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Strategic attention and decision control support prospective memory in a complex dual-task environment

Russell J. Boag[1], Luke Strickland[1], Shayne Loft[1], & Andrew Heathcote[2],

[1]The University of Western Australia

[2]The University of Tasmania

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Abstract

Human performance in complex multiple-task environments depends critically on the interplay between cognitive control and cognitive capacity. In this paper we propose a tractable computational model of how cognitive control and capacity influence the speed and accuracy of decisions made in the event-based prospective memory (PM) paradigm, and in doing so test a new quantitative formulation that measures two distinct components of cognitive capacity (gain and focus) that apply generally to choices among two or more options. Consistent with prior work, individuals used proactive control (increased ongoing task thresholds under PM load) and reactive control (inhibited ongoing task accumulation rates to PM items) to support PM performance. Individuals used cognitive gain to increase the amount of resources allocated to the ongoing task under time pressure and PM load. However, when demands exceeded the capacity limit, resources were reallocated (shared) between ongoing task and PM processes. Extending previous work, individuals used cognitive focus to control the quality of processing for the ongoing and PM tasks based on the particular demand and payoff structure of the environment (e.g., higher focus for higher priority tasks; lower focus under high time pressure and with PM load). Our model provides the first detailed quantitative understanding of cognitive gain and focus as they apply to evidence accumulation models, which – along with cognitive control mechanisms – support decision-making in complex multiple-task environments.

Keywords: cognitive control; cognitive capacity; prospective memory; selective attention; multi-tasking; Bayesian evidence accumulation model

Human performance in complex multiple-task environments depends critically on the interplay between cognitive control and cognitive capacity. *Cognitive control* refers to processes that adapt the cognitive system to meet specific task demands (Braver, 2012; Braver & Barch, 2002; Miller & Cohen, 2001; Miyake et al., 2000). *Cognitive capacity* refers to a finite pool of cognitive resources involved in information processing (e.g., attention, working memory) that can be allocated to various features of the task environment and whose limited nature gives rise to resource bottlenecks (Kahneman, 1973; Navon & Gopher, 1979). In this paper we propose a computational model of how cognitive control and capacity influence the speed and accuracy of decisions made in the event-based prospective memory paradigm, and within that model introduce and validate a new quantitative formulation that identifies two distinct components of cognitive capacity that apply more broadly to making choices among two or more options.

Event-based Prospective Memory (PM) refers to the ability to remember to perform deferred task actions when a particular stimulus or event is encountered in the future (Einstein & McDaniel, 1990). PM tasks often arise in complex, dynamic, and safety critical task environments such as aviation and healthcare (Dismukes, 2012; Grundgeiger, Sanderson, MacDougall, & Venkatesh, 2010; Loft, 2014), in which failures to manage PM demands can have dire consequences (e.g., an airline pilot forgetting to set the flaps before take-off; Dismukes & Nowinski, 2007; an emergency physician forgetting to check the patient's heart rhythm; Soar et al., 2015). As such, there has been a significant effort to understand the cognitive processes involved in PM, and when and why those processes fail (e.g., Einstein & McDaniel, 2005; Hicks, Marsh, & Cook, 2005; Scullin, McDaniel, & Shelton, 2013; Smith & Bayen, 2004; Strickland, Loft, Remington, & Heathcote, 2018).

In a typical PM study, participants perform two tasks: a primary decision-making task (e.g., lexical decision), referred to as the *ongoing task*, and a secondary *PM task* (e.g., press an alternative key for an animal word; Einstein & McDaniel, 1990). In *control blocks* participants perform only the ongoing task. In *PM blocks*, participants perform the same ongoing task, but on some trials will encounter a PM target. Often, individuals are slower to respond to non-target ongoing task items in PM blocks than in control blocks, even when no PM response is required (e.g., Marsh, Hicks, Cook, Hansen, & Pallos, 2003; Smith, 2003). This slowing is referred to as *PM cost* to the ongoing task. The concepts of cognitive control and cognitive capacity have emerged as central to theories regarding the psychological mechanisms underlying costs and PM.

To measure the cognitive control processes and cognitive capacity underlying PM, Strickland et al. (2018) developed a quantitative model, Prospective Memory Decision Control (PMDC). They found that, with a relatively simple ongoing task (lexical decision), PM was supported by proactive and reactive cognitive control mechanisms that delay ongoing decisions relative to PM decisions so that the former do not pre-empt the latter. PMDC indicated no role for *capacity sharing* between monitoring for PM targets and performing the ongoing task, a mechanism often proposed by verbally specified PM theories (e.g., Smith, 2003, Einstein & McDaniel, 2005). Recently, however, Boag, Strickland, Neal, Heathcote, and Loft (2019) applied PMDC to an air traffic control conflict detection task and *did* find evidence for capacity sharing between PM monitoring and ongoing task decisions, likely due to the high cognitive demands of the conflict detection paradigm.

In the current manuscript we fit PMDC to a large-scale experiment in which almost 250 participants attended two-hour sessions of an air traffic control conflict detection task where demands of the PM and ongoing task approached the limit of human capacity. We introduce a formal theory of capacity that maps two features of the PMDC model – the quality and quantity of information processing – to two distinct components of cognitive capacity – gain and focus, in line with neurologically-inspired computational models and neurophysiological data (Carandini & Heeger, 2012). We manipulate gain and focus by varying PM demand, time pressure, and strategic payoffs, while holding bottom-up components of information processing constant (i.e., the task and stimuli have the same perceptual characteristics across experimental conditions). Our model provides the first detailed quantitative understanding of cognitive gain and focus as they apply to evidence accumulation models, which – along with cognitive control mechanisms – can support PM and ongoing task performance in complex dynamic task environments.

Prospective Memory Decision Control

PMDC belongs to the broad class of *evidence accumulation models* (e.g., Brown & Heathcote, 2008; Ratcliff, 1978), which assume that decisions are made by sampling evidence from the environment until an evidence threshold is reached. Evidence-accumulation models provide a comprehensive account of numerous empirical phenomena observed in simple decision-making tasks, including differences in the speed of correct and error responses, speed-accuracy trade-offs, and response biases (see Rae, Heathcote, Donkin, Averell, & Brown, 2014, for perceptual-, lexical-, and memory-based examples). PMDC formalizes decision making as a process of evidence accumulation among independent racing linear ballistic accumulators (LBA; Brown & Heathcote, 2008). In PM paradigms three accumulators are required: two for the ongoing task responses and a third for the PM response. Correct PM responses (i.e., PM hits) occur on PM trials when the PM accumulator reaches threshold before either of the ongoing task accumulators. Incorrect PM responses (i.e., PM misses) occur when one of the ongoing task accumulators reaches threshold before the PM accumulator (Strickland et al., 2018).

Figure 1 shows the PMDC architecture applied to an air traffic control conflict detection task, in which participants decide whether pairs of aircraft will violate a minimum separation standard, with an additional PM requirement. There are three accumulators that correspond to deciding a stimulus is a *conflict*, a *non-conflict*, or a *PM target*. In each accumulator, evidence accrues linearly (arrows in Figure 1), from points on the uniform interval [0-A] (which represent random trial-to-trial biases), until the total in one accumulator reaches its threshold (b), triggering a response. Thresholds are assumed to be set prior to the trial without reference to the nature of the upcoming stimulus in order to avoid circularity (i.e., if thresholds could be altered contingent on the identity of the stimulus there would be no need to accumulate evidence). The rate of evidence accumulation corresponds to the strength of evidence for a response and varies normally from trial to trial with mean v and standard deviation sv. Accumulation rate is determined both by top-down processes (e.g., cognitive capacity devoted to processing the stimulus) and bottom-up factors (e.g., the sensory information available from the stimulus). The time for non-decision processes (e.g., stimulus encoding and motor response execution), t_{er}, is the observed RT minus the decision (evidence accumulation) time.

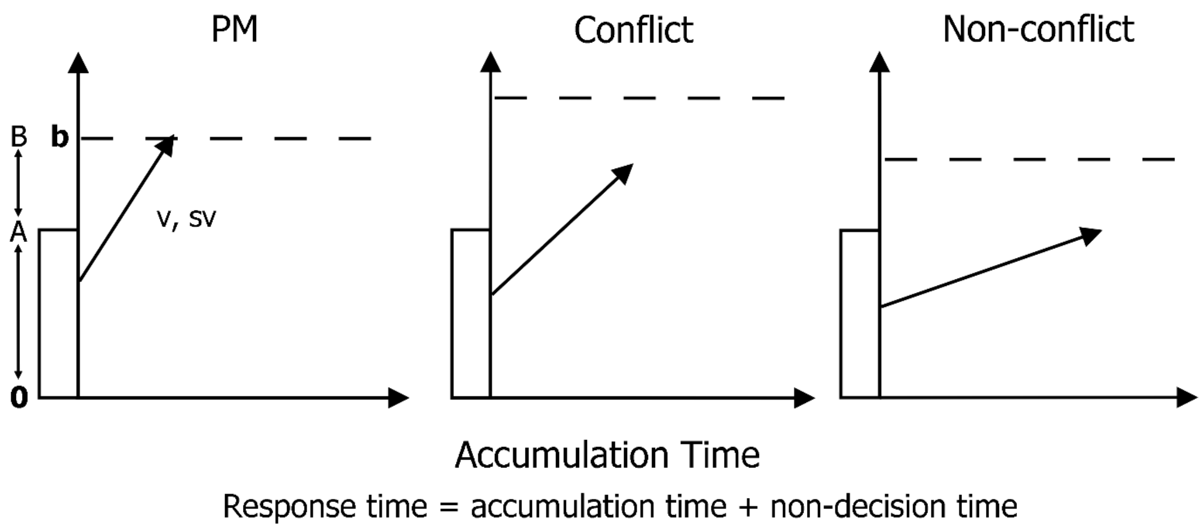

Figure 1. An LBA model of a PM task with a concurrent conflict detection task. Evidence for each response is initially drawn from a uniform distribution on the interval [0, A]. Over time, evidence accumulates towards each response at rates drawn from independent normal distributions with mean v, and standard deviation sv. The first accumulator to reach its threshold, b, determines the overt response. We refer in our results to B, which is $b - A$, where $B > 0$ and so $b > A$. Total RT is determined by accumulation time plus non-decision time.

The aim of fitting PMDC to data is to measure the psychological quantities that underlie performance, and to ascertain what those quantities suggest about cognitive control and cognitive capacity. PMDC instantiates the *proactive* and *reactive* cognitive control mechanisms specified by Braver's (2012) dual-mechanisms theory. Key to the present work, it also provides measures of processing capacity and the degree to which capacity is shared between concurrent tasks. For example, the *quantity* of evidence accumulation is distinct from the *quality* of evidence accumulation. The quantity of accumulation is given by summing the rates for the ongoing-task accumulators, and it mainly determines the overall speed of responding. The quality of accumulation corresponds to the difference between the rates for the accumulator corresponding to the ongoing-task stimulus (the "matching" accumulator) and the accumulator corresponding to the incorrect response (the “mismatching” accumulator), and it mainly determines accuracy. As will be formalized below, we propose a way in which these quantities can be mapped to two distinct components of cognitive capacity: a gain or signal-boost mechanism, which we call *gain capacity*, and a cognitive focus mechanism that improves the signal-to-noise ratio for the choice, which we call *focus capacity*. We now explain how PMDC instantiates these mechanisms and review several benchmark findings regarding proactive and reactive cognitive control in PM, before discussing recent results implicating cognitive capacity in PM.

Proactive and Reactive Control

Proactive control refers to top-down processes used to "bias attention, perception and action systems in a goal-driven manner" (Braver, 2012, p. 2) in advance of a goal-related event, so that they are already active when the event is encountered. According to PMDC, participants can proactively control ongoing task decisions by raising thresholds in PM blocks, so that on PM trials the ongoing-task accumulators are less likely to complete before the PM accumulator, thereby reducing the probability of a PM miss. This follows from the fact that in evidence accumulation models, thresholds are the locus of *a priori* strategies that drive mechanisms such as the speed-accuracy trade-off (Liu & Watanabe, 2012) and response biases (Donkin, Brown, & Heathcote, 2011; Mulder, Wagenmakers, Ratcliff, Boekel, & Forstmann, 2012).

To date, every evidence accumulation modeling study that has compared ongoing task performance between control and PM blocks has found elevated thresholds in the latter, consistent with proactive control (Anderson et al., 2018; Ball & Aschenbrenner, 2017; Boag et al., 2019; Heathcote, Loft & Remington, 2015; Horn & Bayen, 2015; Horn, Bayen, & Smith, 2011, 2013; Strickland et al., 2017, 2018). In Strickland et al. (2018), participants set even higher ongoing task thresholds when instructed that the PM task was important. Participants also exerted control over PM thresholds (i.e., the evidence required to make a PM response) as a function of the importance of the PM task relative to the ongoing task: PM thresholds were reduced when the PM task was important (Strickland et al., 2018).

Reactive control, in contrast, refers to automatic 'stimulus-driven' processes deployed to influence responding "only as needed, in a just-in-time manner" (Braver, 2012, p. 2). Thus, reactive control processes relevant to PM are expected to occur on PM-target trials. The model's reactive control mechanism is depicted in Figure 2.

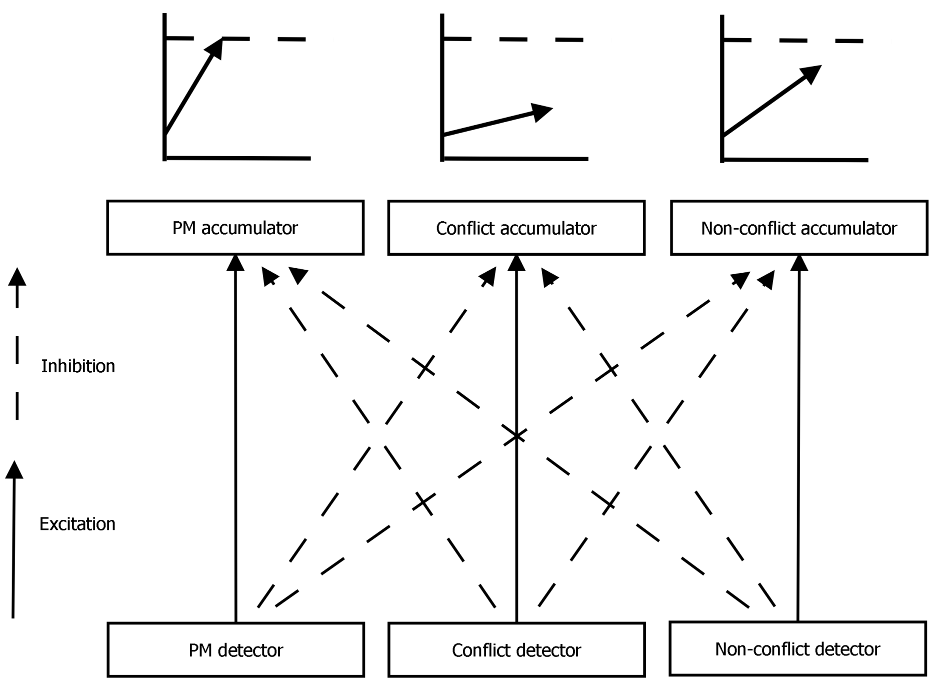

Figure 2. Reactive control of accumulation rates in PMDC, using the example of an air traffic control conflict detection task in which participants have a concurrent PM task. The encoding process includes detectors (rectangles) for each possible response to the task: 'conflict', 'non-conflict', and 'PM'. The detectors receive input from stimulus features. Output from the detectors can directly increase (solid lines) the input to the corresponding evidence accumulator (excitation) or reduce (dashed lines) the input to competing accumulators (inhibition).

As PM stimulus inputs are processed on PM trials, stimulus features consistent with PM excite the PM accumulator, increasing its accumulation rate, while inhibiting other accumulators in a feedforward manner (reactive inhibition), decreasing their accumulation rates. Thus, in addition to PM accumulation being faster on PM trials than non-PM trials, accumulation towards ongoing task decisions should be lower on PM trials than non-PM trials.[1] Consistent with theoretical (Bugg, Scullin, & McDaniel, 2013) and neurological (McDaniel, LaMontagne, Beck, Scullin, & Braver, 2013) work implicating reactive control in PM, recent empirical work has demonstrated that reactive control is critical to PM responses being correctly made when individuals are concurrently making ongoing lexical decisions (Strickland et al., 2018) or while making demanding ongoing air traffic control conflict detections (Boag et al., 2019).

Capacity for PM in Basic Paradigms

Several early studies on capacity for PM in basic paradigms (e.g., Marsh et al., 2003; Smith, 2003) suggested that PM monitoring and retrieval processes can draw attentional focus away from the ongoing task, resulting in increased response latency and/or poorer accuracy for ongoing task responses when under PM load. Moreover, ongoing task performance was most negatively affected by PM tasks involving non-focal PM items (i.e., low overlap between the information that needs to be assessed to detect the PM target and the information that needs to be assessed to perform the ongoing task), tasks with multiple PM items to be remembered, and tasks

[1] Reactive inhibition of rates on PM target trials may appear incompatible with the faster RTs observed in the intention superiority literature (e.g., Marsh, Hicks, & Watson, 2002). However, on PM target trials, accumulators for the ongoing task responses must compete with a much faster PM response accumulator. Overt ongoing task responses on PM trials are therefore more likely to be fast errors that outpace the PM accumulation process, a phenomenon known as statistical facilitation (Raab, 1962). As such, fast PM miss RTs are not incompatible with lower PM miss accumulation rates.

with weak PM item-PM response associations, thus suggesting some degree of capacity sharing between ongoing task and PM processing (Einstein et al., 2005; Marsh et al., 2003).

This early work mostly used the term capacity in a narrative sense (but see Smith & Bayen, 2004), in which a limited capacity resource pool is assumed, and data interpreted based on its properties, without a strict formal justification of capacity or the underlying logical assumptions involved (see Navon, 1984, for a critique of this approach). PMDC takes a measurement approach, in which the accumulation rate parameters are used as a measure of capacity (as have other models for measuring ongoing task capacity in PM; Boywitt & Rummel, 2012; Horn et al., 2011). Rates have been argued to measure capacity because they estimate processing speed, which the majority of attention theory assumes should vary in proportion to the capacity available (e.g., Bundesen, 1990; Gobell, Tseng, & Sperling, 2004; Kahneman, 1973; Navon & Gopher, 1979; Wickens, 1980).[2] Most PM theories assume that PM cost to the ongoing task results from reduced ongoing task capacity, such that monitoring for PM targets draws cognitive resources away from the ongoing task (e.g., Einstein & McDaniel, 2005; Marsh et al., 2003; Smith, 2003). Under this account, PM costs occur when cognitive resources are fully occupied, at which point concurrent tasks are forced to share resources, which is reflected in reduced ongoing task accumulation rates under PM load.

To date, most evidence accumulation modeling of PM costs in basic paradigms has not found changes to the quality or quantity of evidence accumulation to non-PM items across PM

[2] Empirical work also justifies this connection: rates converge with other measures of cognitive capacity (Donkin, Little, & Houpt, 2014; Eidels, Donkin, Brown, & Heathcote, 2010) and manipulations of capacity (e.g., adding a secondary task) have the expected effects on rates (Castro, Strayer, Matzke & Heathcote, 2018; Logan et al., 2014).

and control blocks, suggesting PM processing does not draw cognitive capacity away from the ongoing task (e.g., Ball & Aschenbrenner, 2017; Heathcote et al., 2015; Horn & Bayen, 2015; Strickland et al., 2017, 2018). Given this apparent lack of costs to concurrent processing in basic PM paradigms, a formally grounded theory of capacity for PM has not been explored further. However, as we discuss next, recent work has demonstrated that PM-induced costs to ongoing task information processing *can* occur in paradigms where the ongoing task is sufficiently demanding so as to fully occupy cognitive resources (Boag et al., 2019; Strickland, Elliott, Wilson, Loft, Neal, & Heathcote, 2019). These findings motivate the current article, in which we develop a formal framework for understanding cognitive capacity in PMDC.

PM in Demanding Task Environments

In a cognitively demanding simulation of air traffic control conflict detection, Boag et al. (2019) recently found robust evidence of PM costs to ongoing task accumulation rates. In their task, participants classified stimuli (pairs of aircraft on converging trajectories) as *conflict* or *non-conflict* depending on whether they would violate a 5 nautical mile minimum separation standard during their flight. In PM blocks, some aircraft stimuli were PM targets (aircraft with certain callsigns) that required a *PM* response. PMDC indicated that PM demands affected both the *quantity* and the *quality* of ongoing-task processing. The quantity of ongoing-task processing increased with both time pressure and PM demands, consistent with an increase in the overall availability of resources or cognitive capacity, possibly due to an increase in effort (e.g., Kahneman, 1973). The quality of processing for the ongoing and PM tasks, however, indicated a two-way trade off: ongoing-task quality decreased when PM demand was added (i.e., capacity was diverted from ongoing to PM), but as time pressure increased resources were diverted from the PM task to the ongoing task to compensate for the extra capacity demands generated by working to a shorter deadline (i.e., capacity was diverted from the PM task to the ongoing task).

There is currently no mathematical framework explaining the manner in which Boag et al. (2019) found that ongoing task capacity was affected by PM demands. However, the finding that PM demands induced costs to ongoing-task processing quality, but increased ongoing-task processing quantity, suggests that PM may affect two separable components of ongoing-task capacity. This aligns with current computational and neural theories of selective attentional modulation of information processing (e.g., Carandini & Heeger, 2012; Corbetta & Shulman, 2002; Egner & Hirsch, 2005; Herrmann, Montaser-Kouhsari, Carrasco, & Heeger, 2010; Hillyard, Vogel, & Luck, 1998; Reynolds & Heeger, 2009), which instantiate variable attentional *gain* and *focus* mechanisms corresponding to a broadly-tuned gain or signal-boost mechanism, and a more finely-tuned attentional focus, within a single computational 'normalization' framework (e.g., Reynolds & Heeger, 2009; Schwartz & Simoncelli, 2001). These theories propose that capacity effects arise from the operation of canonical computations that modulate attention (as well as many other perceptual and cognitive processes) at the neural level (see Carandini & Heeger, 2012). This echoes early views of visual attention as a 'spotlight' with variable intensity and focus (called *sensitivity* and *selectivity* by Posner & Boies, 1971) that serve to ensure relevant information in the environment is detected and selected for processing (e.g., Broadbent, 1957; Kahneman, 1973; Posner & Boies, 1971). The key difference between the early non-neurological models and current neural models is that in the latter the canonical mechanisms are assumed to operate on neurons or populations of neurons (e.g., by scaling and sharpening tuning curves that govern firing rate and amplitude; Busse, Wade, & Carandini, 2009; Carandini & Heeger, 2012; Heeger, 1992).

Computer simulations of neural models of selective attention converge with current neurophysiological data on attentional control and modulation in implicating functionally distinct brain regions involved in attentional "amplification" (i.e., gain) and "selective control" (i.e., focus) (Hillyard, Vogel, & Luck, 1998; see also Carandini & Heeger, 2012, and Corbetta & Shulman, 2002). However, these models are currently limited to simulation by 'hand-tuning' parameters and are not easily fit to behavioural data. To bridge this gap between practical quantitative measurement and recent neurologically-inspired process approaches, we present a tractable evidence-accumulation framework for measuring two computational processes (gain and focus) that drive cognitive capacity effects. Our framework includes two components of cognitive capacity: one we term *focus capacity* (C_f), which is the sole determinant of the *quality* of resources allocated among tasks (e.g., ongoing vs. PM), and one we term *gain capacity* (C_g), which primarily controls the quantity of resources deployed, although quantity is also a function of focus capacity. In the next section, we provide a quantitative mapping of gain and focus to the quality and quantity of evidence accumulation. This mapping is generic to any accumulator-based theory of decision making among any number of choices, but we exemplify it here in terms of PMDC's three-choice architecture (i.e., a binary-choice ongoing task with one PM accumulator).

A Dual-Capacity Theory of Accumulator Models

Gain and Focus

Our general modeling architecture consists of a set of $i = 1 \ldots n$ accumulators, each of which receives a specific bottom-up input $I_i \geq 0$ that is monotonic increasing with the match between each accumulator's preferred stimulus and the encoding of that stimulus, and a non-specific input that adds the same amount $1/f$, where $f > 0$, to the bottom-up inputs for all accumulators. Note that as $1/f$ increases, the ability of the accumulators to discriminate inputs decreases. The term f is proportional to top-down attention focus, so increased focus results in better discrimination. Finally, we assume that the sum of the specific and non-specific inputs is multiplied by a top-down cognitive-gain parameter, g, that is the same for all accumulators.

We rescale these inputs into a set of relative bottom-up inputs, $s_i = 1/f + I_i$, which sum to one. Hence the overall input to accumulator i, is $gs_i \geq 0$. Note that we have been working with input as a positive quantity in order to relate it to the idea of capacity, which we assume is a positive quantity with a zero-point defining the value below which capacity cannot be depleted (i.e., where capacity is exhausted). However, we assume that the mean rate of evidence accumulation, v, can range over the real line, and map it to overall input by a logarithmic transformation: $v_i = \ln(gs_i)$.[3]

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[3] Although the logarithmic transformation is a natural choice among smooth and monotonic increasing (i.e., order preserving) functions, and widely used for this purpose in mathematics (Bland, Altman, & Rohlf, 2013), we know of no empirical evidence bearing on the form of this transformation and acknowledge that other choices are possible. The logarithmic choice is responsible for gain having exactly the same effect on all accumulator rates, and hence not affecting rate differences among accumulators (i.e., quality) as $\ln(gs_i) = \ln(g) + \ln(s_i)$.

Capacity Limitation

Our model assumes that the two attention components, f and g, are limited in the sense that $fn + F \leq C_f$ and $gn + G \leq C_g$, where C_f and C_g denote the maximum capacity available for focus and gain, and F and G are focus and gain demands from other cognitive processes. For example, the accumulator system under consideration might support decisions for a binary ongoing task. Suppose that F_C and G_C are the demands associated with a control condition and that having to maintain a PM intent increases these demands by additive amounts F_P and G_P (we note that ongoing and PM tasks are assumed to draw on the same pool of capacity). Suppose further that $fn + F_C < C_f$ and $gn + G_C < C_g$. There are two scenarios when the PM load is added, either

1) $(fn + F_C + F_P) \leq C_f$ and $(gn + G_C + G_P) \leq C_g$, in which case ongoing task performance is unaffected, or
2) $(fn + F_C + F_P) > C_f$ and/or $(gn + G_C + G_P) > C_g$, in which case ongoing task performance is impacted.

Assuming F_P and G_P are fixed under the same PM task load, then under (2) ongoing-task attention focus is reduced to $f' = (C_f - F_C - F_P)/n$, and attention gain to $g = (C_g - G_C - G_P)/n$, so that capacity usage equals C_f and C_g respectively.

Testing Capacity Effects in Binary Accumulators

In the binary case (i.e., a two-choice ongoing task) the difference between accumulator rates (i.e., quality), $v_1 - v_2$, is purely a function of attention focus, f, and unaffected by attention gain:

$$v_1 - v_2 = \ln(gs_1) - \ln(gs_2) = \ln(g) + \ln(1/f + I_1) - \ln(g) - \ln(1/f + I_2)$$

$$= \ln(1/f + I_1) - \ln(1/f + I_2)$$

In particular, if v_1 is the rate for the matching accumulator and v_2 the rate for the mismatching accumulator then $I_1 > I_2$ and $\exp(v_1 - v_2) = (1/f + I_1) / (1/f + I_2)$ is evidently a decreasing function of f, with a minimum at 1 (and hence a rate difference of zero) as f approaches zero and a maximum of I_1/I_2 as f increases (i.e., maximum focus). Hence, if we assume I_1 and I_2 are invariant over two conditions then the one with the larger value of $v_1 - v_2$ must have a larger f. Processing quality (i.e., the difference between matching and mismatching accumulation rates) is thus purely a measure of the cognitive focus directed to the task, with higher quality reflecting increased focus. Note that quality refers specifically to the information determining the ongoing task choice, which is binary. Thus, our derivation focuses on the two-accumulator case (i.e., it does not include the PM accumulator) in order to compare ongoing task processing in the control and PM conditions.

The sum of accumulation rates (i.e., quantity), $v_1 + v_2$, is monotonic increasing in attention gain, g, but it is also a function of f:

$$v_1 + v_2 = 2\ln(g) + \ln(s_1) + \ln(s_2) = 2\ln(g) + \ln(1/f + I_1) + \ln(1/f + I_2)$$

In particular, exponentiating reveals the sum to be a decreasing function of f:

$$\exp(v_1 + v_2) = g^2(1/f^2 + (I_1 + I_2)/f + I_1I_2)$$

Hence, if we assume I_1 and I_2 are invariant over two conditions then the one with the larger value of $v_1 + v_2$ must have a larger g and/or a smaller f.

In summary, for a two-choice ongoing task, processing quality is purely a measure of the cognitive focus directed to that task, with higher quality reflecting greater focus. Processing quantity, in contrast, depends on both gain and focus; higher quantity could reflect increased gain and/or reduced focus. Assuming that the ongoing and PM tasks draw on the same pool of capacity, this formulation allows us to assess the effect of PM demand on gain and focus for our (binary) ongoing task. The next section explains how we propose to test this formulation of gain and focus using PMDC, and it also introduces our predictions derived from the theory.

Current Study

We designed the experiment we report here to test our theory of cognitive gain and focus. To this end, we used the air traffic control conflict detection task that Boag et al. (2019) demonstrated imposed sufficient demands on cognitive capacity. In addition, we included three manipulations intended to affect focus and gain: *PM demand*, *time pressure*, and *task importance*, as discussed further below.

In our task, participants made decisions about whether two aircraft would come into conflict at some point in the future. They were presented with aircraft pairs sequentially (i.e., only two aircraft on screen at a time), cruising at the same altitude and converging on a common intersection. Participants responded to each aircraft pair by pressing the *conflict* or *non-conflict* response key to indicate whether the aircraft would violate the 5 nautical mile (nm) lateral minimum separation standard in the future. In some blocks of trials, in addition to detecting conflicts, participants were required to press an alternative PM response key instead of a conflict or non-conflict ongoing task response for any aircraft with a callsign containing two of the same letter (e.g., APA169, RTR451). This is an ecologically representative PM target, since controllers may need to look out for a specific flight number to perform a deferred task action (e.g., put QF217 in a holding pattern after it reaches a specific waypoint; Loft, 2014). This PM target is *non-focal* to conflict detection (Einstein & McDaniel, 2005), meaning that the evidence required to make PM decisions (i.e., assess aircraft callsign) is not required to make ongoing task (conflict/non-conflict) decisions (e.g., assess the relative airspeed and relative distance of the two aircraft from the common intersection; Vuckovic, Kwantes, Humphreys, & Neal, 2014).

To impose time pressure, we manipulated the number of aircraft pairs that needed to be sequentially responded to (trial load), and the total time available to make that set of responses (trial duration). This combination was used to check whether trial load and time available both induced quantitatively similar time pressure effects, since this is not always the case in work contexts such as air traffic control (Loft, Sanderson, Neal, & Moiij, 2007) and other similar applied tasks (e.g., Hendy, Liao, & Milgram, 1997; Palada, Neal, Tay, & Heathcote, 2018).

To test for differences in capacity for gain and focus we also included a between-subjects manipulation of task importance. Four experimental groups received one of four importance instructions (*neutral*, *PM important*, *ongoing important*, and ongoing-*speed important*) that indicated which task(s) outcomes were most important: the accuracy of both tasks equally, the accuracy of the PM task, the accuracy of the ongoing task, or the speed of the ongoing task. The latter instruction encouraged participants to avoid non-response misses (i.e., failing to respond to all pairs in the allocated time). The neutral importance condition was essentially a full replication of Boag et al.'s (2019) design,[4] with the other three importance conditions differing only by incentive structure.

[4] One difference is that in the current study the neutral group received specific instructions to treat each task equally. No such instruction was given in Boag et al. (2019) because there was only one experimental group.

As outlined in our formulation above, we test for differences in cognitive gain in terms of the quantity (sum of matching and mismatching) of ongoing task accumulation rates. Quantity is an increasing function of gain, reflecting the overall amount of cognitive capacity involved in processing a given task, and has been shown to both increase and decrease to meet task demands (Boag et al., 2019; Rae et al., 2014). In line with previous results, we expect quantity to increase as time pressure increases and to be higher in PM blocks compared with control blocks. Consistent with Boag et al. (2019), we also expect ongoing-task quantity to trade off with PM accumulation rates across different levels of time pressure (i.e., capacity should be shunted from PM to ongoing processes as demands increase); such a trade-off is a critical indicator of capacity sharing (Navon & Gopher, 1979).

The three importance manipulations were included to specifically test our new gain and focus formulation of cognitive capacity. We included the speed-important condition to test our formulation of gain. Our reasoning is that since quantity primarily controls the speed of responding rather than accuracy (which is more a function of *quality*), then we should expect quantity to be highest in the speed-important group compared with the other three importance groups (i.e., neutral, ongoing-important, PM-important). Further, a unique prediction of our framework is that because quantity is also a decreasing function of focus, we expect quantity to decrease for the most important task (i.e., where focus should be greatest). Emphasizing the ongoing task should thus lead to lower ongoing-task quantity relative to the other three groups. Emphasizing the PM task (i.e., shifting focus away from the ongoing task) should *increase* ongoing-task quantity, however, participants may repurpose any additional resources to PM processing, which would increase PM quantity at the expense of ongoing-task resources.

We test for changes in cognitive focus in terms of the quality of evidence accumulation (matching – mismatching accumulator ongoing task rates). Quality measures the cognitive focus directed to a given task and is negatively affected by increases in task demands including PM and time pressure (e.g., Boag et al., 2019; Palada et al., 2018; Rae et al., 2014). Consistent with previous work, we expect ongoing-task quality (focus) will decrease as time pressure increases, due to less time being available to processes the stimulus during the shorter response window, and to be lower in PM blocks compared with control blocks, due to focus being shared between the ongoing and PM tasks.

Our importance manipulations were also intended to test our formulation of focus. The speed-important instruction was intended to increase ongoing task gain and hence reduce quality, consistent with speed emphasis negatively affecting processing quality (Rae et al., 2014). The ongoing- and PM-important instructions were aimed at selectively shifting focus between the ongoing and PM tasks, leading to higher quality processing for the emphasized task (relative to the neutral condition). Specifically, emphasizing the accuracy of the ongoing versus PM tasks should shift the focus of attention (which controls accuracy) between the ongoing and PM tasks without requiring a change in response speed (which is primarily controlled by quantity). Emphasizing the ongoing task should thus increase ongoing-task quality relative to the other three groups, whereas emphasizing the PM task should increase PM accumulation rates (reflecting the greater focus on the PM task) and lead to poorer ongoing-task quality.

In terms of cognitive control mechanisms, we expect that participants will use proactive control of thresholds to manage demands associated with time pressure, setting lower ongoing task thresholds when trial deadlines are short to avoid misses (Boag et al., 2019), and higher thresholds when deadlines are long to improve accuracy (Ratcliff & Rouder, 1998). Similarly, we expect that participants will set higher ongoing task thresholds in PM blocks than in control blocks (i.e., proactive control), and that the amount of proactive control will decrease as time pressure increases, because higher levels of time pressure induce a trade-off between raising thresholds to give the PM accumulator more time to finish and lowering thresholds to respond within the trial deadline (Boag et al., 2019). We also expect participants to set lower PM thresholds when under high time pressure in order to ensure that a PM response, if appropriate, is made before the response deadline. Following Strickland et al. (2018), we expect that increasing the importance of the PM task will lead participants to set higher ongoing task thresholds, and that participants will set lower PM thresholds in PM-important versus PM-unimportant conditions.

In terms of reactive control, we expect 'reactive excitation' in which PM accumulation rates are higher on PM target trials than on non-PM trials. We also expected inhibition of ongoing task accumulation rates on PM target trials (Strickland et al., 2018). That is, accumulation rates for conflict and non-conflict decisions should be lower on PM target trials, as compared with non-PM trials in PM blocks. Previous work suggests that reactive control is not affected by time pressure (Boag et al., 2019), but that it can be adjusted in line with the relative importance of the PM and ongoing tasks, as Strickland et al. (2018) found that reactive inhibition increased when the importance of the PM task was emphasized compared with when the ongoing task was emphasized. This is also in line with fMRI data showing that motivating participants via rewards can increase the strength of reactive response inhibition (Boehler et al., 2014).

Method

Participants

Two-hundred and forty-six people participated across four between-subject conditions (see Table 1). Age ranged from 18 to 57 years. Participants completed one two-hour testing session. All procedures were approved by the University of Western Australia Human Research Ethics Office.

Table 1

Participant summary

	N participants	Mean (SD) age
Neutral Condition	62 (47 female)	20.94 (3.99)
Ongoing-important Condition	60 (41 female)	22.20 (7.41)
Speed-important Condition	60 (49 female)	22.85 (5.28)
PM-important Condition	64 (48 female)	24.24 (10.28)

Air Traffic Control Conflict Detection Task

The conflict detection task (Fothergil, Loft, & Neal, 2009) was designed using principles of representative design to achieve a balance of task fidelity, generality, and experimental control. The task has been used previously to study PM (Loft, 2014) and to develop and test a performance theory and computational model of expert conflict detection in air traffic control (Loft et al., 2009). As illustrated in Figure 3, each trial of the air traffic control conflict detection task presented a single pair of aircraft traversing a fictitious en-route sector. The total area of the airspace was 180 nm (nautical miles) by 112.5 nm. A data block next to each aircraft displayed the callsign, the aircraft type, the flight level, and the speed in knots (i.e., nautical miles per hour). Aircraft appeared within a circular air traffic control sector with a neutral grey background and flew straight orthogonal paths (indicated by black lines) that converged at the centre of the display. Aircraft position was updated every 20 ms. Participants could not alter the flight levels, velocities, or headings of the aircraft.

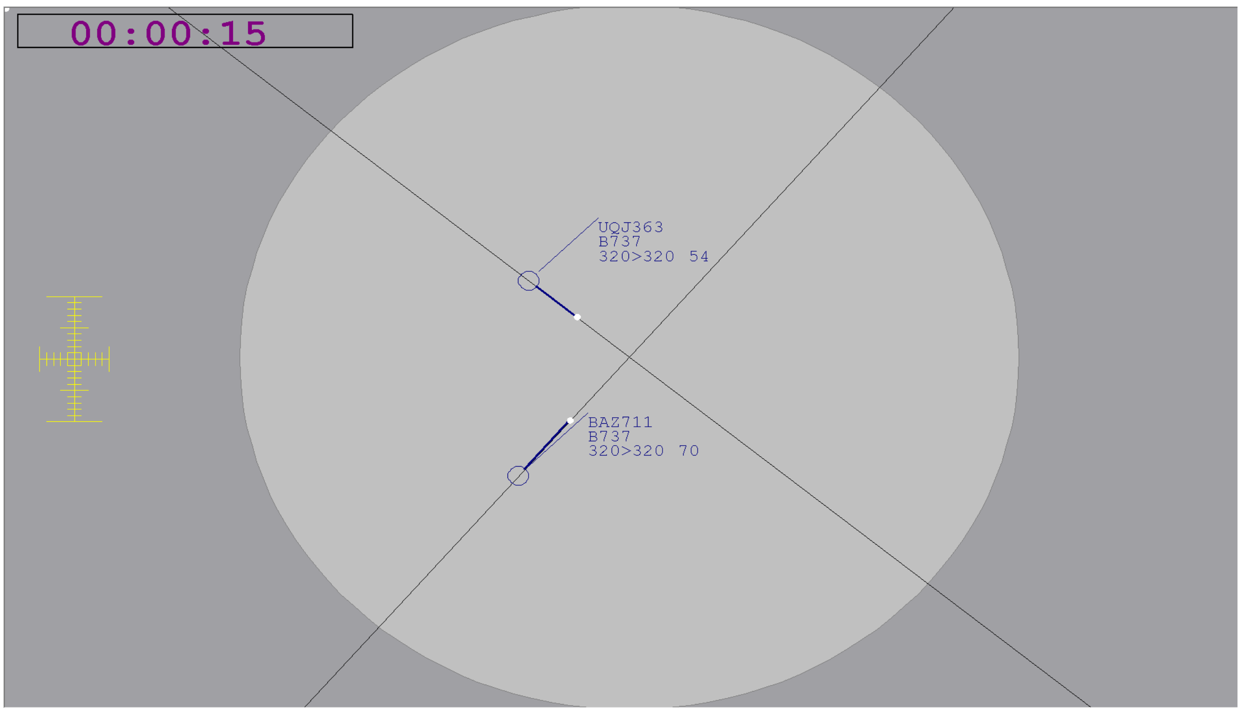

Figure 3. Air traffic control simulator display. Information blocks next to each aircraft show callsign (e.g., UQJ363), aircraft type (B737), current and cleared altitude (e.g., 320>320), and airspeed (e.g., 54). Note that the airspeed indicator omits the ending zero of the true speed (e.g., '54' stands for 540 knots). The countdown timer indicates that there are 15 seconds remaining in the trial.

Participants' primary (ongoing) task was to classify each pair of aircraft as either 'conflict' or 'non-conflict' depending on whether the aircraft would violate a 5 nm minimum separation distance at some point during their flight. On some trials one of the two aircraft would also contain a PM target feature which required participants to make a PM response instead of the conflict or non-conflict ongoing task response. Pairs of aircraft were presented sequentially and disappeared from the screen once a response was made. A countdown timer showed the seconds remaining in each trial. Trials ended when the timer reached zero. Any remaining aircraft not responded to would disappear and be recorded as non-responses. A probe vector line on each aircraft indicated the aircraft's heading and predicted position one minute into the future. A 10 nm by 20 nm (approximately 2 cm by 4 cm on screen) scale marker was fixed on the left side of the display for use as a reference for judging relative aircraft distance.

Experimental Stimuli and Design

Table 2 gives the range of values for the features of aircraft pairs and the distribution they were drawn from. We fixed the angle of approach between aircraft at 90 degrees to avoid interactions between angle and perceived conflict status (e.g., Vuckovic, Kwantes, & Neal, 2013). The flight level for all aircraft was fixed at 37,000 feet. To create the different conflict and non-conflict stimuli, each aircraft pair was assigned a miss distance (d_{min}: the distance between the aircraft at their point of closest approach) either less than or greater than the 5 nm separation standard. For conflict stimuli, d_{min} values were drawn from the uniform distribution [0,3] nm. For non-conflict stimuli, d_{min} values were drawn from the uniform distribution [7,10] nm. We allowed the speed, direction of approach, time to minimum separation (t_{min}), and order of passing at the crossing (i.e., faster aircraft first vs. slower aircraft first) to vary randomly (within the ranges specified in Table 2) from trial to trial to ensure participants could not learn to use these features as predictive cues (Bowden & Loft, 2016; Loft, Humphreys, & Neal, 2004).

Table 2

Range of spatial variables of aircraft stimuli

Spatial variable	Lower	Upper	Units
d_{min} (Conflicts)	0	3	nm
d_{min} (Non-conflicts)	7	10	nm
Airspeed	400	700	knots
Direction of approach	0	360	degrees
t_{min}	120	210	seconds
Order of passing	0	1	0 = fastest first, 1 = slowest first

Aircraft with callsigns containing two of the same letter (e.g., APA169, RTR451) were PM targets. On PM target trials only one of the aircraft on screen ever contained a PM target, never both. Participants were instructed to respond to PM targets by pressing an alternate PM key (e.g., *'j'* or *'d'*) instead of the ongoing task (conflict/non-conflict) keys.

As illustrated in Table 3, participants performed four sets of trials, each containing a block of control trials and a block of PM trials. Block order (control- or PM-first) was counterbalanced between participants. In control blocks, participants were presented with a randomized sequence of 80 aircraft pairs (40 conflict and 40 non-conflict), with no PM targets. In PM blocks, participants were presented with a randomized sequence of 240 aircraft pairs (120 conflict and 120 non-conflict). Of these, a random 48 (24 conflict and 24 non-conflict) contained a PM target. Thus, 20% (48/240) of PM block stimuli were PM targets. As raised in the General Discussion section, this is a higher ratio of PM target trials to ongoing task trials than is traditionally used in PM studies, but gives us more PM trials, which serve to reliably constrain our model, and increase the accuracy and precision of fitting PMDC to data.

Table 3

Details of experimental blocks with number of control and PM stimuli presented

Trial load (decisions per trial)	Trial duration (s) (overall time available)	Time pressure (s) (average time available per decision)	Control block trials	PM block trials
2	12	6	80	240
2	8	4	80	240
5	20	4	80	240
5	10	2	80	240

To create time pressure (average available time per conflict detection decision), we manipulated trial load (decisions per trial) and trial duration (total time available to respond to all decisions within a trial). Each trial had a load of either 2 or 5 aircraft pairs presented with an associated trial duration (see Table 3). This resulted in 4 unique trial-load by trial-duration combinations; one with 6s per decision, two blocks with 4s per decision and one block with 2s per decision. The order in which blocks were presented was counterbalanced across participants. We note that trial load and trial duration were not crossed orthogonally. This was done intentionally to ensure trial load and trial duration remained at a reasonably engaging level of demand while also not becoming impossibly difficult. Participants were informed of the trial load and trial duration before each block and could thus adjust their strategies accordingly.

In addition, we included a between-subjects manipulation of task importance. The four conditions received one of four importance instructions (neutral, ongoing-important, speed-important, PM-important) that indicated which task to focus on (e.g., the accuracy of both tasks equally, PM task accuracy, ongoing task accuracy, ongoing task speed) and the associated incentive structure (see Procedure for more details).

Procedure

Our procedure was identical to Boag et al. (2019), except that we included an additional between-subjects manipulation of task importance. Each testing session comprised a training phase and a test phase, which took 2 hours in total to complete. During the training phase participants received verbal task instructions, watched an on-screen demonstration of the task, and completed 40 training trials that included feedback after each response. The PM task was not included in training. During the experimental phase participants completed eight blocks of experimental trials without feedback.

Participants responded to each aircraft pair by pressing either the *conflict* or *non-conflict* key. Participants were informed that each aircraft pair would be presented sequentially and contain two aircraft moving towards each other on converging flight paths with a crossover point at the centre of the display. They were told that several spatial properties of the aircraft would vary from trial to trial, including their starting distance from the central crossing point, relative speed, and distance of minimum separation. Before each block of trials, participants saw visual instructions reminding them of the trial load and trial duration for that block. Depending on the block, participants then received either control or PM instructions. Before control blocks, participants were instructed that they only needed to make conflict and non-conflict responses. Before PM blocks, participants were instructed to press a PM response key instead of the conflict or non-conflict keys when they detected a PM target.

In addition, each condition received one of four task importance instructions (neutral, ongoing-important, speed-important, PM-important). The neutral condition was instructed to "*place equal importance on performing all aspects of the task accurately*" and shown a points table in which correct (incorrect) ongoing task and PM responses were rewarded (penalized) equally. The ongoing-important condition was told to "*place primary importance on performing the conflict detection task accurately*" and shown a points table in which ongoing task rewards and penalties were double those of the PM task. The speed-important condition was instructed to "*place primary importance on avoiding non-response misses*" and shown a points table in which the penalty for non-responses was double the penalty for ongoing task and PM errors. The PM-important condition was told to "*place primary importance on performing the 'call-sign' (PM) task accurately*" and shown a points table in which PM task rewards and penalties were double those of the ongoing task. The relevant importance instruction was also displayed on a sign on the participant's desk as a reminder. As an additional incentive to follow the instructions, participants were told they could win up to $5 based on their score (all participants were given $5 upon completing the task regardless of score). Participants completed a short distractor task and saw a final reminder to respond as quickly and accurately as possible before commencing the block.

Using a standard QWERTY keyboard, four response key assignments were counterbalanced across participants; 1) *s* = conflict, *d* = non-conflict, *j* = PM, 2) *d* = conflict, *s* = non-conflict, *j* = PM, 3) *k* = conflict, *j* = non-conflict, *d* = PM, and 4) *j* = conflict, *k* = non-conflict, *d* = PM. Participants were instructed to rest their fingers on their particular response key combination throughout the task so that we could assume equal motor response time in our modeling (see Voss, Voss, & Klauer, 2010). Each trial was preceded by a screen with the text 'Press [Space] to continue', pressing the space-bar initiated the trial. Trials ended when the trial deadline expired (i.e., when the timer reached zero). Any aircraft pairs not responded to within the deadline were recorded as non-responses. Besides the training trials, participants received no further feedback about their performance. Participants took self-paced breaks between each block of trials and were permitted short breaks at any point between trials as needed.

Results

We first report conventional statistical analyses to check whether our experimental manipulations had the expected effects on RT, accuracy, and non-response (miss) rate. Excluded data are summarized in Table S1 in the supplementary materials. We excluded trials with outlying RTs, defined as less than 0.2s or greater than 3 times the inter-quartile range / 1.349 (a robust measure of standard deviation) above the mean, censoring outliers separately by time pressure and importance instruction. We also excluded non-response misses and PM responses to control-block ongoing-task stimuli (Table S1). Incorrect ongoing task responses to PM items (~1% of responses) were included in model fitting but are not analysed further. For each importance condition, conventional statistical analyses compare mean accuracy and RT by stimulus type (conflict, non-conflict, PM), PM block (control, PM), and time pressure. Because trial load and trial duration were not crossed orthogonally, time pressure is compared separately for each level of trial load. At low trial load (2 decisions per trial) we compared time pressures of 6 and 4 seconds per decision; at high trial load (5 decisions per trial) we compared time pressures of 4 and 2 seconds per decision. Between-subjects analyses are used to assess the effects of our importance manipulation.

We used generalized linear mixed models with a probit link function in our significance testing for accuracy effects. We used general linear mixed models with a Gaussian link function in our significance testing for mean correct RTs. Analyses were conducted using the R package *lme4* (Bates, Machler, Bolker, & Walker, 2015). Significance was assessed using Wald's chi-square tests (Fox & Weisberg, 2011) with a two-tailed alpha level of .05. Post hoc tests applied Bonferroni's correction for alpha inflation. The results of our analyses are tabulated in the supplementary materials (Tables S2-S8). All standard errors reported in text and displayed in graphs were calculated using Morey's (2008) within-subject bias-corrected method.

Conflict Detection (Non-PM Stimuli) Trials

For all four importance groups, conflict detection accuracy was lower for conflicts compared with non-conflicts and slightly lower under PM load compared with control (Table 4). Conflict detection accuracy decreased as time pressure increased, under both low trial-load and high trial-load (Table 5). We note that this effect did not reach significance for the ongoing-important group when under low-load. That this effect disappears when the ongoing task was prioritized suggests higher capacity for the ongoing task that is modulated by importance (we explore this effect further in the Model Summary section below). When comparing cells with equal time pressure, conflict detection accuracy was not significantly affected by trial load for any of the importance groups.

Table 4

Mean (SE) ongoing task accuracy (%).

	Stimulus		PM Block		Time Pressure/Trial Load			
Most Important Task	Conflict	Non-conflict	Control	PM	A	B	C	D
Neutral	71.1 (2.2)	83.2 (2.1)	77.4 (2.4)	76.9 (2.5)	80.4 (1.8)	78.1 (1.8)	78.5 (2.0)	71.7 (2.1)
Ongoing	75.0 (2.3)	80.0 (2.3)	78.4 (2.3)	76.6 (2.5)	79.5 (2.0)	78.5 (1.7)	79.1 (1.9)	72.9 (2.0)
Speed	71.8 (2.3)	77.3 (2.3)	75.9 (2.3)	73.2 (2.4)	78.0 (1.9)	74.9 (1.9)	75.6 (1.8)	69.6 (1.9)
PM	73.4 (2.6)	80.1 (2.6)	78.1 (2.4)	75.4 (2.8)	80.2 (2.1)	77.2 (2.1)	78.2 (1.9)	71.5 (2.3)

A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

Table 5

Ongoing task accuracy (%) time pressure contrasts

	A-B					B-C					C-D				
Most Important Task	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*
Neutral	2.29	3.12	61	**.003**	0.40	-0.34	-0.47	61	0.64	0.06	6.71	8.84	61	**<.001**	1.12
Ongoing	0.98	0.94	59	0.35	0.12	-0.58	-0.82	59	0.41	0.11	6.23	7.07	59	**<.001**	0.91
Speed	3.10	4.13	59	**<.001**	0.53	-0.60	-0.80	59	0.43	0.10	5.96	6.35	59	**<.001**	0.82
PM	2.98	4.29	63	**<.001**	0.54	-0.96	-1.24	63	0.22	0.16	6.62	8.18	63	**<.001**	1.02

Bold values indicate significance at alpha = .05 (two-tailed). A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

There was a significant interaction between PM block and time pressure on conflict detection accuracy, such that the cost to accuracy in PM blocks (as compared to control blocks) was greatest when trial load and time pressure were high (Table 6). We note that this effect was most pronounced in the PM-important group. Conflict detection accuracy did not differ significantly by importance (Tables 14 & 15).

Table 6

Ongoing task accuracy (%) and RT (s) cost contrasts

	Difference between PM and control blocks during high time pressure and high load									
	Accuracy (%)					RT (s)				
Most Important Task	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*
Neutral	3.18	3.81	61	**<.001**	0.48	-0.29	-10.68	61	**<.001**	1.36
Ongoing	3.47	3.90	59	**<.001**	0.50	-0.29	-9.05	58	**<.001**	1.18
Speed	3.81	3.91	59	**<.001**	0.50	-0.25	-7.48	59	**<.001**	0.97
PM	5.00	5.74	63	**<.001**	0.72	-0.39	-13.35	62	**<.001**	1.68

Bold values indicate significance at alpha = .05 (two-tailed).

In general, mean RT was slower for conflicts compared with non-conflicts, slower for errors compared with correct responses, and slower during PM blocks than control blocks (Tables 7 & 8). Mean RTs were significantly faster under higher time pressure for both low trial-load and high trial-load conditions (Table 9). Mean RTs were also slower under high trial load compared with low trial load when comparing cells with equal time pressure, although this effect was small and did not reach significance for the ongoing- and speed-important groups. For the neutral and speed-important groups there was as significant interaction between PM block and time pressure on mean ongoing task RT (Table S3), such that the cost to PM block RT became smaller as time pressure increased. This effect was not significant for the ongoing- and PM-important groups. Mean RT was fastest in the speed-important group; RTs were around 180ms faster on average than the other three importance groups (Tables 14 & 15).

Table 7

Mean (SE) ongoing task RT (s)

	Stimulus		PM Block		Time Pressure/Trial Load			
Most Important Task	Conflict	Non-conflict	Control	PM	A	B	C	D
Neutral	2.91 (0.15)	2.51 (0.13)	2.49 (0.13)	2.93 (0.14)	3.45 (0.11)	2.67 (0.07)	2.84 (0.08)	1.89 (0.06)
Ongoing	2.94 (0.15)	2.67 (0.13)	2.60 (0.14)	3.01 (0.13)	3.57 (0.10)	2.80 (0.07)	2.93 (0.08)	1.91 (0.06)
Speed	2.77 (0.15)	2.52 (0.13)	2.43 (0.13)	2.87 (0.14)	3.35 (0.11)	2.65 (0.08)	2.78 (0.08)	1.80 (0.06)
PM	2.97 (0.14)	2.68 (0.12)	2.58 (0.13)	3.07 (0.13)	3.58 (0.10)	2.76 (0.06)	2.98 (0.08)	1.98 (0.06)

A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

Table 8

Ongoing task correct and error RT contrasts

	Ongoing Task						PM Task					
	Mean RT (s)						Mean RT (s)					
Most Important Task	Correct	Error	*t*	*df*	*p*	*d*	Correct	Error	*t*	*df*	*p*	*d*
Neutral	2.80	2.93	-10.26	21436	**<.001**	0.10	1.74	2.56	-34.21	3391.9	**<.001**	0.95
Ongoing	2.89	3.01	-8.22	20264	**<.001**	0.09	1.83	2.63	-33.56	4545.8	**<.001**	0.83
Speed	2.75	2.77	-1.71	25599	.088	0.02	1.79	2.46	-29.56	4445.4	**<.001**	0.73
PM	2.91	3.01	-7.77	23104	**<.001**	0.08	1.69	2.59	-33.46	2773.4	**<.001**	1.07

Bold values indicate significance at alpha = .05 (two-tailed).

Table 9

Ongoing task RT (s) time pressure contrasts

	A-B					B-C					C-D				
Most Important Task	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*
Neutral	0.78	9.88	61	**<.001**	1.25	-0.17	-3.15	61	**.003**	0.40	0.95	15.78	61	**<.001**	2.00
Ongoing	0.78	9.98	59	**<.001**	1.29	-0.13	-2.09	59	.041	0.27	1.02	16.63	58	**<.001**	2.17
Speed	0.71	6.96	59	**<.001**	0.90	-0.14	-1.69	59	0.10	0.22	0.98	15.65	59	**<.001**	2.02
PM	0.82	14.99	62	**<.001**	1.89	-0.20	-3.43	62	**.001**	0.43	0.99	14.98	62	**<.001**	1.89

Bold values indicate significance at alpha = .05 (two-tailed). A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

To summarize, the addition of PM load resulted in slower (*Mean Difference* = 0.45s) and slightly less accurate (*Mean Difference* = 1.93%) conflict detection, while increased time pressure led to faster (*Mean Difference* = 0.99s) but less accurate (*Mean Difference* = 4.39%) conflict detection. Importance affected mean RT, such that conflict detection RT was fastest with speed-important instructions, but there were no reliable effects of importance on accuracy.

PM Trials

PM responses were scored correct if the participant pressed the PM response key instead of an ongoing task (conflict/non-conflict) response key on PM target trials. For all four importance groups, PM accuracy decreased as time pressure increased, during both low trial-load and high trial-load conditions (Tables 10 & 11). Except for the neutral group, PM accuracy was not significantly affected by trial load when comparing cells with equal time pressure. PM accuracy was highest (by around 10%) in the PM-important group and lowest in the ongoing- and speed-important groups (Tables 14 & 15). As will be discussed further in the Model

Summary section below, this suggests higher capacity for the PM task when it was emphasized, indicating that importance directs how resources are allocated between tasks.

Table 10

Mean (SE) PM accuracy (%)

	Stimulus		Time Pressure/Trial Load			
Most Important Task	PM (Conflict)	PM (Non-conflict)	A	B	C	D
Neutral	77.4 (2.6)	74.3 (2.6)	84.7 (1.5)	76.0 (1.9)	80.9 (1.5)	61.7 (1.9)
Ongoing	68.5 (3.0)	67.3 (3.1)	78.2 (1.9)	71.6 (1.7)	72.7 (1.5)	49.0 (2.2)
Speed	70.6 (2.8)	69.2 (2.8)	78.3 (1.8)	73.1 (1.7)	72.7 (2.1)	55.4 (1.9)
PM	80.2 (2.0)	77.7 (2.2)	86.5 (1.2)	79.6 (1.4)	81.1 (1.3)	68.6 (1.7)

A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

Table 11

PM accuracy (%) time pressure contrasts

	A-B					B-C					C-D				
Most Important Task	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*
Neutral	8.63	5.14	61	**<.001**	0.65	-4.90	-2.73	61	**.008**	0.35	19.20	10.90	61	**<.001**	1.38
Ongoing	6.64	2.79	59	**.007**	0.36	-1.18	-0.63	59	0.53	0.08	23.72	9.92	59	**<.001**	1.28
Speed	5.19	2.48	59	**0.016**	0.32	0.41	0.17	59	0.87	0.02	17.31	6.76	59	**<.001**	0.87
PM	6.90	5.50	63	**<.001**	0.69	-1.52	-0.95	63	0.34	0.12	12.52	7.81	63	**<.001**	0.98

Bold values indicate significance at alpha = .05 (two-tailed). A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

Mean RT was slower for PM errors compared with correct PM responses (in PM blocks) (Table 12). Mean RT for correct PM responses was significantly faster at higher levels of time pressure during both low trial-load and high trial-load conditions (Tables 12 & 13). PM RT was not significantly affected by trial load when comparing cells with equal time pressure. There were no significant differences in PM accuracy or PM RT between conflict PM targets and non-conflict PM targets. PM false alarms (i.e., PM responses to non-PM stimuli in PM blocks) occurred on around 0.6% of PM block trials in each importance group (see Table S1) with mean RTs around 2.30s (Neutral: 2.27s, Ongoing-important: 2.16s, Speed-important: 2.33s, PM-important: 2.39s). PM false alarms were most common in the PM-important group and least common in the neutral group (*Mean Difference* = 0.55%) t = 1.88, df = 63.96, p = .065, d = 0.33. PM RT was fastest in the PM-important group and slowest in the ongoing-important group (Tables 14 & 15).

To summarize, as with the ongoing task, increased time pressure led to faster (*Mean Difference* = 0.27s) but less accurate PM performance (*Mean Difference* = 12.51%), whereas PM-importance instructions led to faster and more accurate PM performance.

Table 12

Mean (SE) PM RT (s)

	Stimulus		Outcome		Time Pressure/Trial Load			
Most Important Task	PM (Conflict)	PM (Conflict)	Correct	Error	A	B	C	D
Neutral	1.76 (0.06)	1.76 (0.06)	1.75 (0.07)	2.75 (0.16)	1.99 (0.05)	1.74 (0.03)	1.79 (0.05)	1.49 (0.04)
Ongoing	1.87 (0.07)	1.87 (0.07)	1.85 (0.08)	2.75 (0.16)	2.06 (0.05)	1.85 (0.04)	1.90 (0.04)	1.60 (0.05)
Speed	1.81 (0.06)	1.81 (0.06)	1.82 (0.07)	2.60 (0.16)	2.06 (0.04)	1.82 (0.04)	1.86 (0.04)	1.52 (0.04)
PM	1.72 (0.05)	1.72 (0.05)	1.72 (0.07)	2.81 (0.18)	1.96 (0.05)	1.69 (0.03)	1.73 (0.03)	1.51 (0.04)

A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

Table 13

PM RT (s) time pressure contrasts

	A-B					B-C					C-D				
Most Important Task	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*
Neutral	0.27	5.34	60	**<.001**	0.68	-0.05	-1.24	61	0.22	0.16	0.25	5.66	60	**<.001**	0.73
Ongoing	0.21	4.32	56	**<.001**	0.57	-0.07	-1.59	56	0.12	0.21	0.30	4.95	55	**<.001**	0.66
Speed	0.24	5.02	57	**<.001**	0.66	-0.04	-0.76	57	0.45	0.10	0.33	5.84	57	**<.001**	0.77
PM	0.28	5.35	61	**<.001**	0.68	-0.05	-1.56	60	0.12	0.20	0.21	7.50	59	**<.001**	0.97

Bold values indicate significance at alpha = .05 (two-tailed). A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

Table 14

Mean (SE) accuracy (%), RT (s), and non-response proportions (%) by importance

	Most Important Task			
Most Important Task	Neutral	Ongoing	Speed	PM
Ongoing Accuracy	77.2 (1.0)	77.5 (1.0)	74.5 (1.0)	76.8 (1.1)
PM Accuracy	76.2 (0.4)	68.4 (0.2)	70.3 (0.2)	79.2 (0.3)
Ongoing RT	2.71 (0.06)	2.80 (0.06)	2.65 (0.06)	2.83 (0.06)
PM RT	1.75 (0.03)	1.85 (0.03)	1.82 (0.02)	1.72 (0.02)
Non-response %	4.3 (0.5)	5.45 (0.5)	3.77 (0.4)	5.67 (0.6)

Table 15

Accuracy (%), RT (s), and non-response proportion (%) importance contrasts

	Task Importance Contrast														
	PM-Ongoing					PM-Speed					Ongoing-Speed				
Measure	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*
Ongoing Accuracy	-0.7	0.58	121.92	.57	0.10	2.2	-1.60	117.29	.11	0.29	2.9	-2.13	114.49	.035	0.39
PM Accuracy	10.8	-3.02	118.93	**.003**	0.54	9.0	-2.65	121.64	**.009**	0.48	-1.8	0.51	116.68	.61	0.09
Ongoing RT	0.02	-0.30	119.90	.77	0.05	0.18	-2.37	120.63	**.019**	0.43	0.16	-2.14	116.92	.035	0.39
PM RT	-0.15	2.75	92.62	**.007**	0.52	-0.12	2.69	108.43	**.008**	0.49	0.02	-0.45	104.04	.65	0.09
Non-response %	0.7	-0.09	112.86	0.93	0.02	1.7	-2.10	108.53	.038	0.37	1.6	-2.45	117.3	**.016**	0.45

Bold values indicate significance at alpha = .05 (two-tailed).

Non-responses

We examined the effects of PM block and time pressure on non-response (miss) proportions using a linear mixed effects model with a probit link function (Table S7 in the supplementary materials). Non-responses included non-responses to PM and ongoing task stimuli. In all four importance groups, non-responses were slightly more frequent in PM blocks compared with control blocks and became more frequent as time pressure increased during both low trial-load and high trial-load conditions (Tables 16 & 17). The proportion of non-responses was higher during low trial load versus high trial load when comparing cells with equal time pressure. There was a significant interaction between PM block and time pressure on non-responses, such that the increase in non-responses from control to PM blocks was greatest when trial load and time pressure were both high. Non-responses were least frequent in the speed-important group (3.8%) and most frequent in the ongoing- and PM-important groups (5.5% and 5.7%) (Tables 14 & 15).

Table 16

Mean non-responses (%) by PM block, time pressure and importance

	PM Block		Time Pressure/Trial Load				
Most Important Task	Control	PM	A	B	C	D	Total %
Neutral	3.84	4.46	1.48	3.17	1.77	10.80	4.30
Ongoing	4.66	5.71	1.54	4.67	2.54	13.04	5.45
Speed	3.32	3.92	1.38	3.59	1.40	8.71	3.77
PM	4.64	6.01	1.44	4.59	3.13	13.53	5.67

A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

Table 17

Non-response (%) time pressure contrasts

	A-B					B-C					C-D				
Most Important Task	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*	Mean Diff.	*t*	*df*	*p*	*d*
Neutral	-1.31	-4.02	61	**<.001**	0.51	1.13	3.14	61	**.003**	0.40	-8.50	-7.92	61	**<.001**	1.01
Ongoing	-2.81	-6.13	59	**<.001**	0.79	1.97	3.76	59	**<.001**	0.49	-10.10	-8.23	59	**<.001**	1.06
Speed	-1.89	-3.30	59	**.002**	0.43	1.82	3.14	59	**.003**	0.41	-6.78	-5.31	59	**<.001**	0.69
PM	-2.63	-4.17	63	**<.001**	0.52	1.02	2.30	63	**.025**	0.29	-9.66	-7.24	63	**<.001**	0.91

Bold values indicate significance at alpha = .05 (two-tailed). A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

Model Analysis

We fit PMDC using a conventional parameterization in terms of separate mean rate (*v*) estimates for each accumulator. We could have directly parameterized mean rates as functions of gain and focus, but rather than imposing this framework we sought instead to test its implications using the conventional rate estimates to calculate quality (i.e., the difference in mean rates between matching and mismatching accumulators for the ongoing task) and quantity (i.e., the sum of mean rates over matching and mismatching accumulators).

Within-subjects (i.e., within each importance condition), model parameters were allowed to vary over latent response (i.e., the conflict, non-conflict, and PM accumulators that lead to each response) and three manifest factors: stimulus type, time pressure/trial load, and PM block. Note that the latent response factor corresponds to the accumulators, not the observed response, meaning that the observed response is predicted by the model, not included in it. There were four stimulus types: *non-PM conflict*, *non-PM non-conflict*, *PM conflict*, and *PM non-conflict*. There were four levels of time pressure, created by manipulating trial load (2 vs. 5 decisions per trial) and trial duration: 6s per decision (2 decisions per trial), 4s per decision (2 decisions per trial), 4s per decision (5 decisions per trial), 2s per decision (5 decisions per trial). There were two levels of PM demand: *control* (i.e., no PM demand) and *PM*.

To reduce model complexity, we applied a number of theoretically sensible restrictions on which experimental factors each parameter could vary over. As is common practice, we estimated one common *A* parameter for all accumulators and conditions. We allowed the *sv* parameter to vary by stimulus and accumulator but not by time pressure or PM block.[5] Since one accumulator parameter must be fixed to an arbitrary value as a scaling parameter (Donkin, Brown, & Heathcote, 2009), we fixed the *sv* parameter for PM responses to non-PM items at 0.5.

Since our design minimized any potential differences in the motor movement required to make each response (i.e., participants kept their fingers positioned above the response keys), one non-decision time (t_{er}) parameter was estimated for each participant. Moreover, previous research has suggested that non-decision time does not play a role in PM cost for the LBA (e.g., Anderson et al., 2018; Heathcote et al., 2015; Strickland et al., 2017, 2018). Owing to very low numbers of PM false alarms (PM responses to non-PM stimuli in PM blocks), estimates of both accumulation rate and variance (v and sv) were pooled across time pressure and PM blocks to give one PM rate for PM responses to non-PM items and one corresponding *sv* parameter (which was used as a fixed scaling parameter as mentioned above) for each importance group. These constraints resulted in an 89 parameter most flexible 'top' model with one A, one t_{er}, 20 B, 57 v, and 10 *sv* parameters. We compared this top model against several simpler variants that we outline below (see Model Selection).

[5] We note that this approach is more flexible than most prior LBA modeling, in which *sv* is typically only allowed to vary as a function of whether the latent accumulator is a 'match' or a 'mismatch' to the stimulus (but see Heathcote & Love, 2012; Osth, Bora, Dennis, & Heathcote, 2017; Strickland et al., 2018, for exceptions). We used this more flexible approach because in our model there are two types of 'correct' response for PM trials (i.e., correct PM and correct ongoing task decision). A version of the model constrained to have only one sv parameter (75 parameters in total) produced visually similar fits and either preserved or exaggerated the direction of all effects found in the more flexible model.

Sampling

Model parameters were estimated via Bayesian estimation using Heathcote et al.'s (2018) DMC software, which gives probability distributions that reflect the degree of certainty surrounding parameter values. Because of the large number of participants in our sample and the complexity of our models, hierarchical methods proved too computationally expensive to fit (estimated at several months of multi-core server time per fit), so we estimated parameters separately for each participant.

In Bayesian analysis, the researcher is required to specify prior beliefs about the probabilities of parameters and the form of their distributions before observing the data. However, because of our large sample sizes and use of inference based on posterior probability distributions, the influence of our particular choice of priors on the final parameter estimates was negligible as we used relatively non-informative priors (Table 18), identical to Boag et al. (2019). All prior values were the same over control and PM blocks, the same over time pressure, and the same for each importance group.

Table 18

Prior distributions

Parameter	Distribution	Mean	SD	Lower	Upper
A	Truncated normal	3	1	0	10
B	Truncated normal	2	1	0	None
v (Matching ongoing task response)	Truncated normal	1	2	None	None
v (Mismatching ongoing task response)	Truncated normal	0	2	None	None
v (PM hit)	Truncated normal	1	2	None	None
v (PM false alarm)	Truncated normal	0	2	None	None
sv	Truncated normal	0.5	1	0	None
t_{er}	Uniform		1	0.1	1

We estimated posterior parameter distributions using the differential evolution Markov-chain Monte-Carlo (DE-MCMC) algorithm (Turner, Sederberg, Brown, & Steyvers, 2013). DE-MCMC is especially adept at handling models with highly correlated parameters, as is common in accumulate-to-threshold modelling. The number of chains used by the sampler was three times the number of parameters (e.g., for an 84-parameter model there were 252 chains per parameter). Chains were thinned by 20 (i.e., one iteration out of every 20 was kept) and sampling continued until a Gelman's (2014) multivariate potential scale reduction factor less than 1.1 indicated convergence, stationarity, and mixing. Convergence, stationarity, and mixing were verified via visual inspection. For each participant, the posterior distribution for each parameter consisted of 30,240 samples (i.e., 252 chains with 120 iterations each).

Model Results

Model Fits: Accuracy and RT

To evaluate fit, we sampled 100 posterior predictions for each participant and then averaged over participants. The model provided good fits to both ongoing task and PM accuracy (Figures S1 & S4 in the supplementary materials) and gave a good account of the entire distribution of RTs (Figures S2-S4). The model provided a close fit to the differences in manifest accuracy and RT observed across PM and control blocks and across different levels of time pressure for each importance group. The model also provided accurate out-of-sample predictions of non-response proportions across all experimental factors (Figure S5).

Model Selection

To assess whether we could justify constraining model parameters over experimental factors (e.g., PM block, time pressure) to obtain a simpler model with fewer parameters, we used the Deviance Information Criterion (DIC; Spiegelhalter, Best, Carlin, & Van Der Linde, 2002). The DIC measure considers both the complexity of a model (i.e., the number of parameters) and its goodness of fit. Models with smaller DIC values are typically to be preferred. The number of parameters for each model and its DIC value are shown in Table 19.

Using the fully flexible top model as a starting point, we built several simpler variants by systematically constraining ongoing task threshold and ongoing task rate parameters over time pressure and PM block. We could thus establish whether it was necessary to vary ongoing task thresholds and/or rates to account for the observed effects of time pressure and PM demand. We compared four simpler variants to the top model: a model in which rates could vary across PM and control blocks but thresholds could not; a model in which thresholds could vary across PM and control blocks but rates could not; a model in which rates could vary by time pressure but thresholds could not; and a model in which thresholds could vary by time pressure but rates could not.

Table 19

DIC model selection. Lower DIC indicates more preference for the model.

		DIC – minimum DIC			
Model	Parameters	Neutral	Ongoing	Speed	PM
Top model	89	303	178	491	495
Selected model	84	**0**	**0**	**0**	**0**
Thresholds fixed over PM block	81	5668	4371	4988	6821
Rates fixed over PM block	73	1549	1644	1674	2267
Thresholds fixed over time pressure	74	4008	4380	5819	4234
Rates fixed over time pressure	47	5925	6616	6188	5822

The DICs for the selected model were: Neutral = 238899, Ongoing = 247298, Speed = 246239, PM = 247860.

As illustrated in Table 19, the fully flexible top model was preferred over each simpler variant, which suggests that it is necessary to allow both ongoing task threshold and ongoing task rate parameters to vary over time pressure and PM demand factors. That is, both parameters play an important role in explaining the empirical effects of time pressure and PM demand.

To further explore whether we could simplify the top model, we tested an additional model (the selected model) that – like the top model – allowed both ongoing task thresholds and ongoing task rates to vary over both time pressure and PM demand factors, but contained a slight simplification in which the PM rate parameter was constrained to not vary by stimulus type (i.e., the same PM rate was estimated for PM conflicts and PM non-conflicts). This simplification makes sense because the evidence used to make PM decisions was independent of the evidence used to make either conflict or non-conflict ongoing task decisions. This model obtained the smallest DIC value of all the models tested and was thus selected as our preferred model for further analysis. The results of model selection thus implicate both rates and thresholds in explaining why ongoing task and PM accuracy and RT differ by time pressure and PM load.

Model Summary

In order to summarize the parameters at the group level, we created a subject-average posterior distribution. To obtain this distribution, we computed the mean of each posterior sample across participants for each parameter. In terms of theory, our main interest was in the accumulation rate and threshold parameters for the ongoing and PM tasks (explored in detail in the following sections). All other parameters had reasonable values consistent with prior studies. The *sv* posterior means and SDs are summarized in Table S9 in the supplementary materials. For non-PM stimuli, ongoing task *sv* parameters were lower for the matching accumulators than the mismatching accumulators, consistent with other LBA modelling (e.g., Heathcote et al., 2015; Heathcote & Love, 2012). PM *sv* was generally more variable than ongoing task *sv*, likely due to the smaller number of PM observations. Table S10 shows the means of the subject-average posterior distribution for non-decision time, *A*, and the PM accumulation rate for PM responses to non-PM items for each importance group. We note that non-decision time was reliably faster in the speed-important group compared with the other three importance groups and slowest in the PM-important group. As will be addressed further in the discussion, this is consistent with some modulation of encoding and motor responses by task importance.

We tested the direction and magnitude of differences in ongoing task and PM threshold and rate parameters for the selected model between conditions to assess how consistent the effects were with our theoretical predictions concerning time pressure, PM demand, and task importance. To this end, we calculated posterior distributions of the differences between experimental conditions. To test the proactive control account of PM costs, for example, we took the difference between ongoing-task thresholds in control blocks and ongoing-task thresholds in PM blocks for each posterior sample, which gives the posterior probability distribution of the effect of PM load on ongoing task thresholds. We calculated differences for each participant independently, before averaging over participants to produce a subject-averaged posterior difference distribution. To assess significance of the differences we report Bayesian *p*-values (Klauer, 2010) for each subject-averaged difference distribution that give the one-tailed probability that the effect does not run in the most sampled direction.

Because of the high ratio of trials per participant in our design, most of the observed differences between parameters had *p*-values close to zero, suggesting a very high probability of an effect being present. To compare the magnitude of the effects, however, we report the standardized difference between parameters (i.e., *M* / *SD* of the posterior difference distribution). Our posterior parameter distributions were approximately normal in shape, so this value can be interpreted analogously to a *Z*-score. As such, we refer to this statistic as *Z* herein. Tables S11-S21 in the supplementary materials display the *Z*-score effect sizes and *p*-values for all parameter comparisons.

Proactive Control

Figure 5 shows ongoing task thresholds (averaged over accumulators) plotted by PM block and time pressure for each importance-instruction group. Ongoing task thresholds were higher in PM than control blocks for both conflict and non-conflict accumulators (Table S11). In both control and PM blocks, average ongoing task thresholds decreased as time pressure increased, under both low trial-load and high trial-load conditions (Table S12). Average ongoing task thresholds also tended to be slightly lower in high trial-load compared to low trial-load conditions when comparing cells with equal time pressure, although the opposite trend occurred in the speed-important control block, and the effect was not reliable for the PM-important group. These effects suggest that participants use thresholds adjustments to adapt to PM and time pressure demands, consistent with proactive cognitive control.

Time pressure affected the amount that participants increased their ongoing task thresholds by when under PM load. That is, the size of ongoing task threshold adjustments between control and PM blocks became smaller as time pressure increased. As shown in Figure 4, the average size of PM block-control block threshold differences tended to be smaller under high time pressure versus low time pressure during both low trial-load and high trial-load conditions, although this effect sometimes did not reach significance at low time pressure (see Table S13). PM block-control block ongoing task threshold differences also tended to be smaller during high trial load versus low trial load when comparing cells with equal time pressure. The amount of proactive control was also affected by task importance, such that the PM-important group used the largest amount of proactive control, while the ongoing- and speed- important groups used the least (all between-subjects importance effects are summarized in Figure 8 and Table 20 below).

Figure 4 also shows PM thresholds under different levels of time pressure for low trial-load (2 decisions per trial) and high trial-load (5 decisions per trial) conditions for all four importance groups. As can be seen, PM thresholds decreased substantially under high time pressure relative to low time pressure during both low trial-load and high trial-load conditions, but tended to not differ much by load when comparing cells with equal time pressure (Table S14). Consistent with the increase in PM false alarms in the PM-important group, PM thresholds were lower during PM-important instructions compared with the other three importance conditions (Figure 4; see also Figure 8), particularly under high time pressure and high load (Table 20). Overall, these shifts in PM thresholds with time pressure support a proactive control account in which participants set thresholds strategically in order to manage responses as a function of time pressure as well as to increase the probability of responding to high- versus low-importance stimuli. However, as noted, this strategy can reduce PM accuracy (under high time pressure) and increase PM false alarms (when PM is important).

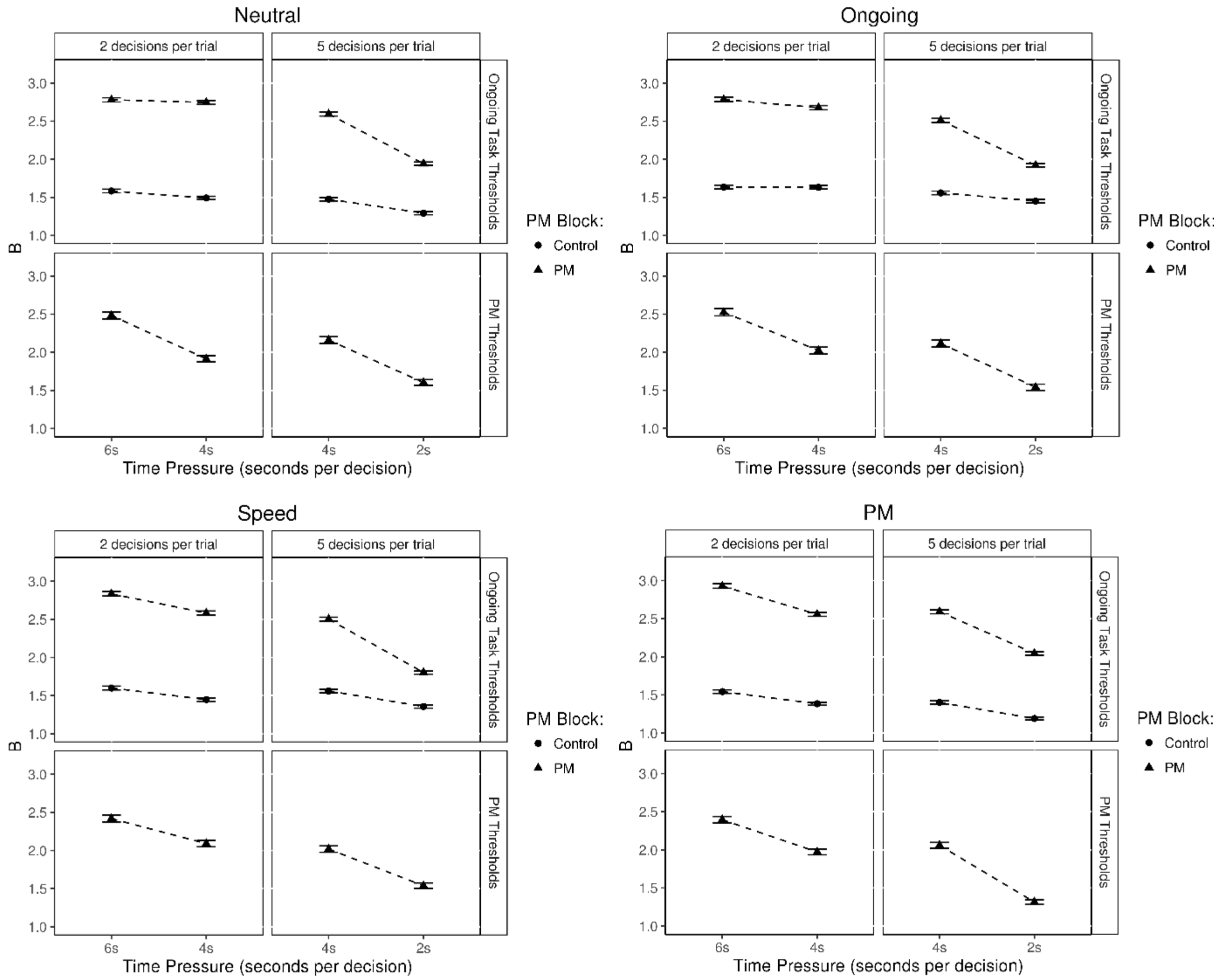

Figure 4. Average ongoing task and PM thresholds by time pressure and PM block for each importance group. Central symbols represent posterior means. Error bars represent +/- 1 posterior standard deviation.

Capacity Effects (Quantity and Quality)

Quantity. As Figure 5 shows, ongoing task accumulation rates increased as time pressure increased. To assess changes in processing quantity with time pressure, we compared the sum of matching and mismatching ongoing task rates in lower time pressure blocks with the sum of matching and mismatching rates in higher time pressure blocks. Processing quantity (matching + mismatching rates) increased from lower to higher time pressure blocks under both low trial-load and high trial-load conditions (Table S15). Quantity decreased, however, from low to high trial load when comparing cells with equal time pressure.

We also investigated how PM demands affected ongoing-task quantity. Ongoing task quantity (matching + mismatching rates) increased from control to PM blocks (Table S16), suggesting that more resources were deployed to the ongoing task under PM demand. Adding PM load thus had a similar effect to increasing time pressure, such that participants deployed more resources under PM load and as the time available to complete the task decreased.

Confirming our framework's prediction that quantity should be a decreasing function of focus, quantity was lowest in the ongoing-important group (where ongoing task focus was highest) and highest in the speed-important group (where ongoing task focus was lowest) (Figure 8 & Table 20). The latter effect is consistent with quantity being primarily related to the speed of responding (in contrast to quality, which represents the signal-to-noise ratio of the evidence and thus determines accuracy).

As shown in Figure 5, the PM accumulation rate decreased with time pressure under both low trial-load and high trial-load conditions, although this was not significant for the speed- or PM-important group at low trial load (possibly reflecting the overall emphasis on task response speed in the first case, and the extra resources shunted to the PM task in the second) (Table S17). PM accumulation rates tended to be lower during high versus low trial load when comparing cells with equal time pressure, although this trend only reached significance for the neutral group. Overall, the PM rate effects suggest a time-pressure modulated trade-off in how resources were allocated between the ongoing and PM tasks: as the ongoing task consumes more resources to cope with additional time pressure demands, it draws on resources that would have otherwise been allocated to the PM task.

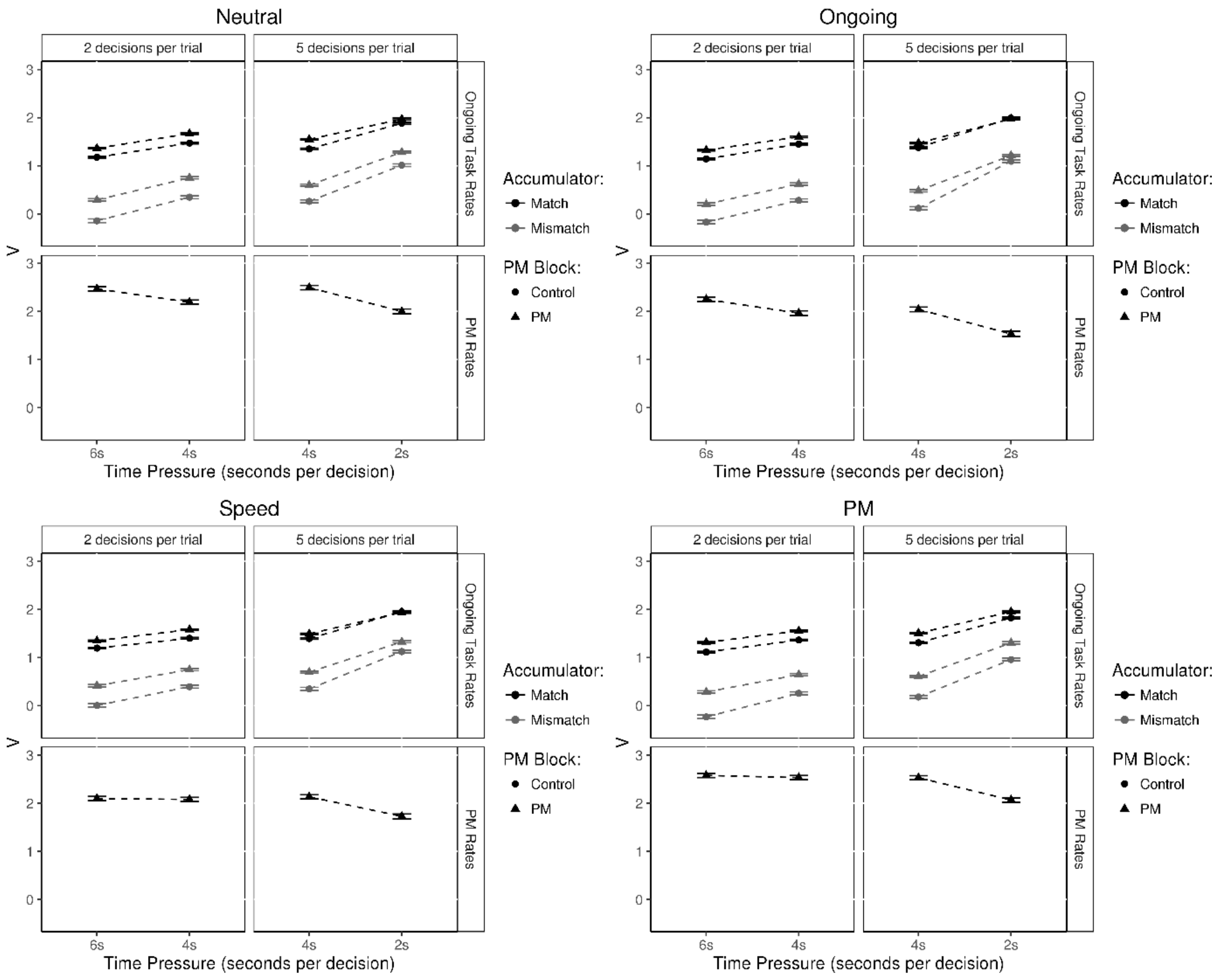

Figure 5. Average ongoing task and PM accumulation rates by time pressure and PM block for each importance group. Central symbols represent posterior means. Error bars represent +/- 1 posterior standard deviation.

Importance also affected PM accumulation rates, such that PM rates were reliably higher in the PM-important group compared with the other three importance conditions (Table 20). PM rates were reliably lower in the ongoing- and speed-important groups compared with neutral and PM-important (Figure 8). As will be discussed, this is consistent with participants directing more resources to PM when the PM task is important and less resources to PM when the ongoing task or response speed is more important.

Quality. We tested for changes in ongoing-task processing quality at different time pressure by comparing the difference between matching and mismatching ongoing task accumulation rates in lower time pressure blocks with the difference between matching and mismatching rates in higher time pressure blocks. Ongoing task rates (i.e., rates for conflicts and non-conflicts that were not PM targets) at different time pressure are illustrated in Figure 5 for each importance group. Except for conflicts presented in low trial-load blocks, the quality of ongoing-task processing was lower in higher time pressure blocks compared with lower time pressure blocks during both low trial-load and high trial-load conditions (Table S18). Increased time pressure thus reduced the quality of ongoing-task processing. This effect was also evident between-subjects, such that overall ongoing-task quality was reliably lower in the speed-important group compared with the other three importance conditions (Figure 8). Processing quality was, in general, not reliably affected by trial load when comparing cells with equal time pressure.

We also tested how ongoing-task quality varied with PM demands. Consistent with capacity-sharing, the difference between matching and mismatching rates was smaller under PM load compared with the control condition (Table S19). That is, the quality of ongoing-task processing was poorer in PM blocks compared with control blocks. There was no significant interaction between time pressure and PM block on ongoing-task quality. In contrast to processing *quantity*, which was highest in the speed-important group, ongoing-task *quality* was highest in the ongoing-important group and lowest in the speed-important group (Figure 6). As will be discussed, this is consistent with our conceptualization of quality as a measure of selective cognitive focus that serves to increase accuracy (which we would expect to be shifted around based on task importance) and quantity as measuring a more general gain mechanism that serves to increase speed (which is less easily directed towards individual task components).

Interestingly, when comparing ongoing-task quality between neutral and PM-important groups, quality tended to be lower under PM-important instructions, but this effect only approached reliability in PM blocks (Table 20). This is also consistent with importance-modulated selective attention and demonstrates selective influence for this model mechanism (i.e., we would only expect PM-importance instructions to take effect in PM blocks). As summarized in Figure 6, together these results suggest that resources are flexibly allocated between competing task goals based on the time pressure, PM load, and relative importance characteristics of the task environment, and provide further support for the idea that capacity involves distinct selective cognitive focus and gain mechanisms.

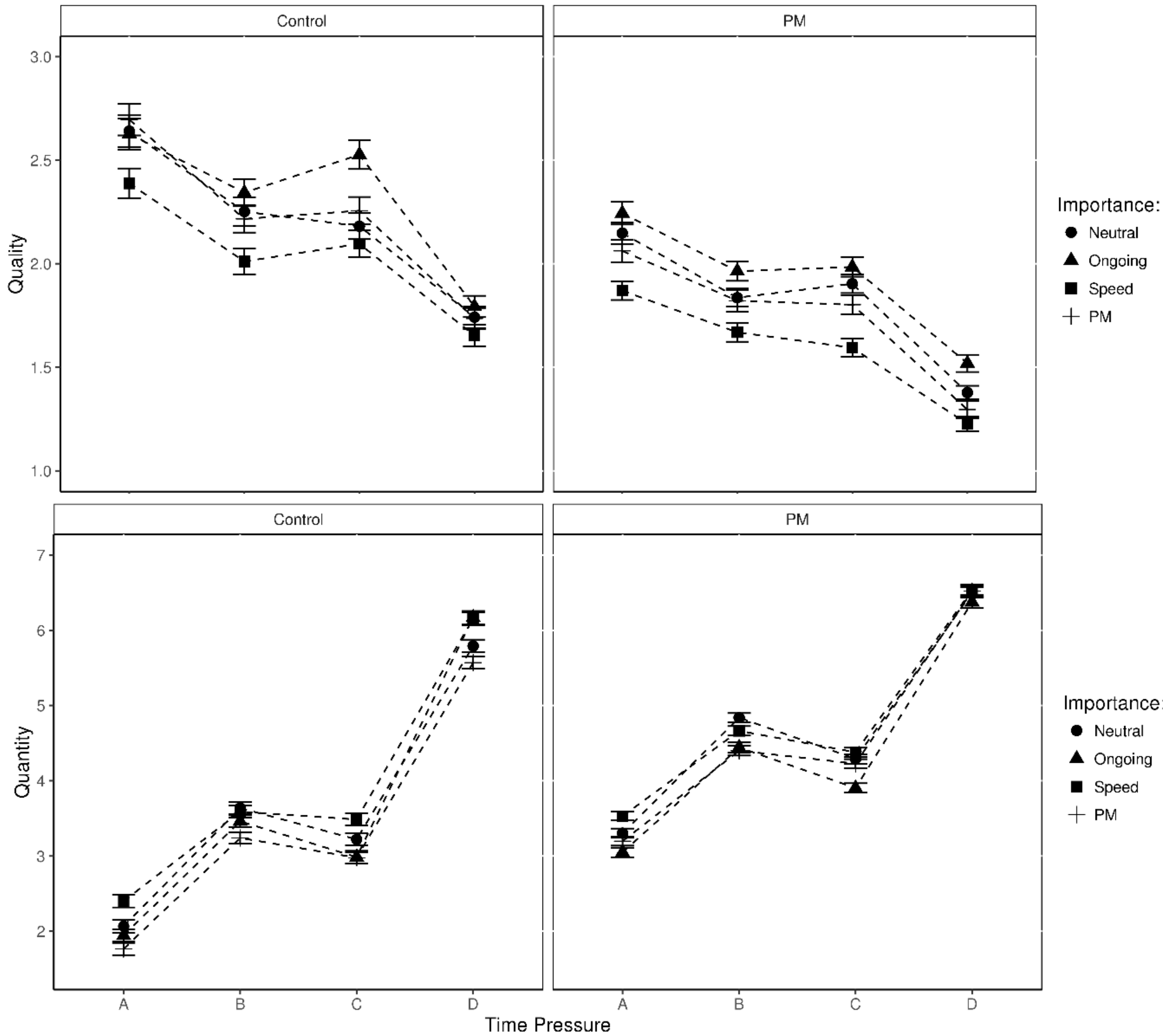

Figure 6. Quality (top) and quantity (bottom) of ongoing-task processing by time pressure and PM block for each importance group (shown as separate lines). Central symbols represent posterior means. Error bars represent +/- 1 posterior standard deviation. A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

Reactive Control (PM vs. Non-PM Trial Accumulation)

As illustrated in Figure 7, ongoing task rates were lower for stimuli containing a PM target compared with stimuli that did not contain a PM target (Table S20). This is consistent with reactive inhibition in which accumulation rates for competing ongoing task responses are suppressed in the presence of a PM target.

In general, the strength of the reactive control effect did not interact with time pressure, with a mixture of positive, negative, and non-significant effects (see Table S21). Overall, however (and considering the small effect sizes involved) it appears that reactive control processes were mostly unaffected by changes in time pressure.

In contrast, the strength of reactive control was affected by task importance. As illustrated in Figure 8, the average amount of reactive control (i.e., the strength of inhibition of ongoing task stimuli) was highest under PM-important instructions (replicating Strickland et al., 2018) and lowest under ongoing-important instructions (Table 20). This suggests that importance modulates the strength with which irrelevant task information is inhibited.

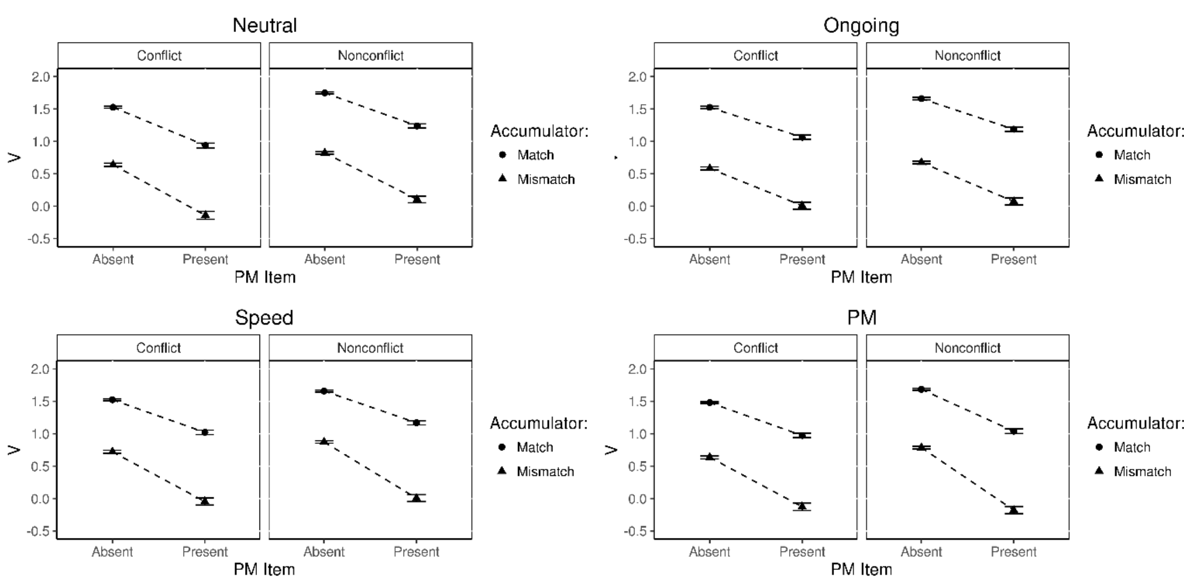

Figure 7. Ongoing task accumulation rates with PM item present versus absent for each importance group. Central symbols represent posterior means. Error bars represent +/- 1 posterior standard deviation.

Table 20

Between-subjects importance contrasts

		Task Importance Contrast							
		PM-Neutral		PM-Ongoing		Ongoing-Speed		Ongoing-Neutral	
Measure	Condition	Z	*p*	Z	*p*	Z	*p*	Z	*p*
Mean Proactive Control	A	4.57	**<.001**	5.52	**<.001**	-2.01	**.02**	-1.11	.13
	B	-2.15	**.02**	3.33	**.001**	-2.22	**.01**	-5.29	**<.001**
	C	1.94	**.03**	6.22	**<.001**	0.26	.40	-4.30	**<.001**
	D	6.65	**<.001**	11.75	**<.001**	0.68	.25	-5.62	**<.001**
Mean Reactive Control	A	0.44	.33	2.59	**.005**	-2.72	**.004**	-2.18	**.01**
	B	1.07	.14	3.23	**.001**	-3.08	**.001**	-2.23	**.01**
	C	2.46	**.006**	2.97	**.001**	-0.34	.37	-0.61	.27
	D	0.97	.17	5.11	**<.001**	-3.8	**<.001**	-4.34	**<.001**
Mean PM *B*	A	-1.41	.08	-2.04	**.02**	1.63	**.05**	0.62	.27
	B	1.05	.15	-0.90	.18	-1.12	.13	1.83	**.03**
	C	-1.75	**.04**	-0.99	.16	1.60	.06	-0.72	.23
	D	-5.76	**<.001**	-4.34	**<.001**	0.04	.48	-1.12	.13
Mean PM *v*	A	1.81	**.03**	5.45	**<.001**	2.56	**.005**	-3.62	**<.001**
	B	5.61	**<.001**	8.82	**<.001**	-1.77	**.04**	-3.47	**<.001**
	C	0.56	.29	7.65	**<.001**	-1.48	.07	-6.97	**<.001**
	D	1.00	.16	7.62	**<.001**	-2.63	**.005**	-6.26	**<.001**
Mean Quantity	Control	-3.87	**<.001**	-3.29	**.001**	-3.37	**.001**	-0.50	.31
	PM	-2.18	**.02**	2.06	**.02**	-4.70	**<.001**	-4.16	**<.001**
Mean Quality	Control	0.38	.35	-1.65	**.049**	4.93	**<.001**	2.03	**.02**
	PM	-1.54	.06	-3.90	**<.001**	7.51	**<.001**	2.36	**.008**
Non-decision time		3.08	**.002**	-3.29	**.001**	-3.37	**.001**	-0.50	.31

Bold values indicate reliable effects (*p*s denote the Bayesian one-tailed probability that the effect does not run in the most sampled direction). A: 6s per decision, 2 decisions per trial; B: 4s per decision, 2 decisions per trial; C: 4s per decision, 5 decisions per trial; D: 2s per decision, 5 decisions per trial.

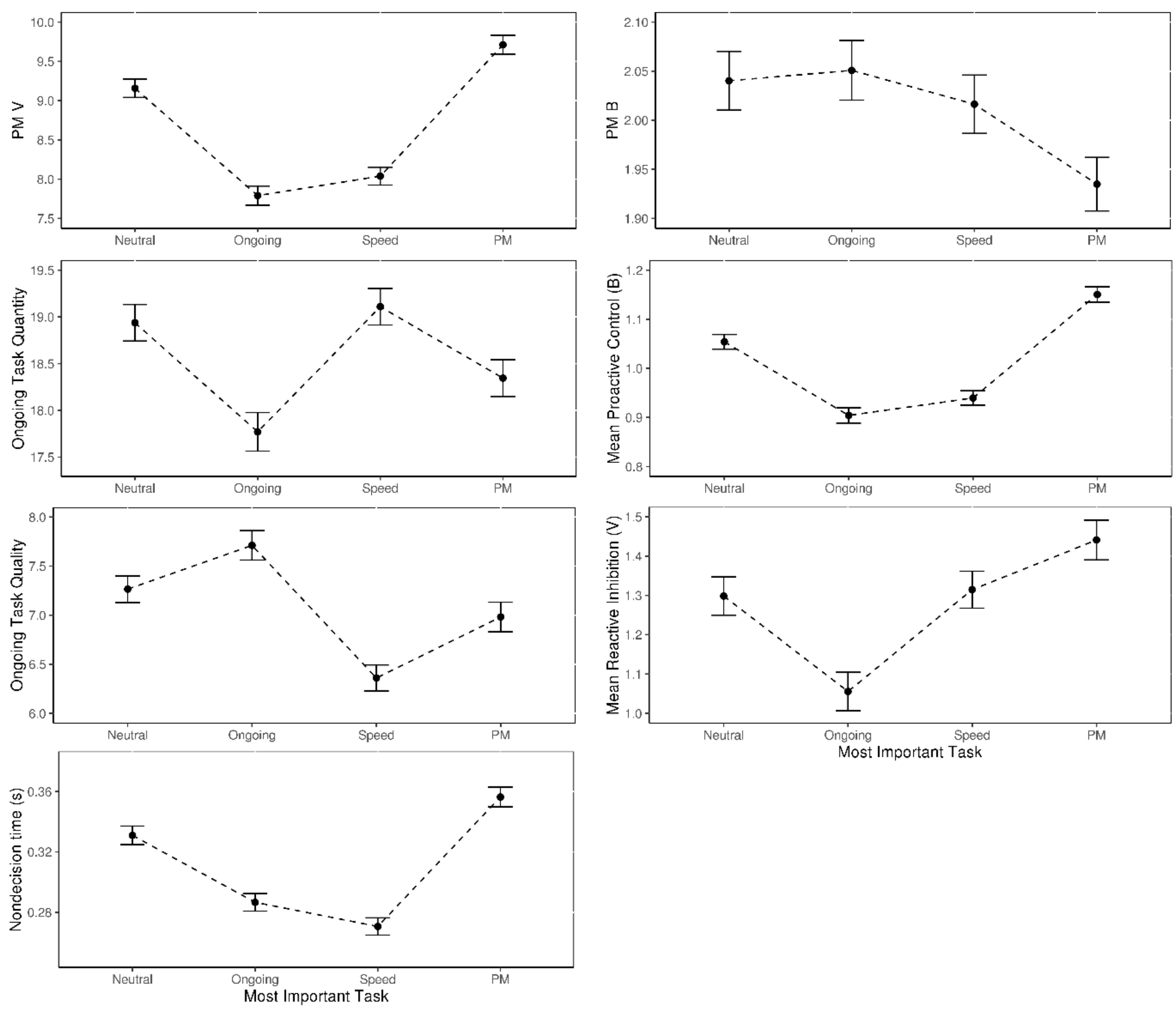

Figure 8. Summary of between-subjects importance effects. The panels on the left show capacity (PM *v*, ongoing-task quantity, ongoing-task quality) and non-decision time effects. The panels on the right show cognitive control effects (PM thresholds, mean proactive control, mean reactive control).

Relative Effects

We assessed the individual contribution to observed accuracy and RT of key model parameters and mechanisms to gain insight into their relative influence on observed behaviour. Our method involved comparing posterior predictions for all time pressure and PM effects for the selected model with the predictions generated from models with parameters averaged over either PM or time pressure blocks (see the Supplementary Materials for full details). The model exploration indicated that ongoing-task accumulation rates explained more of the effect of time pressure on ongoing-task RT than did ongoing-task thresholds, whereas thresholds explained more of the effect of time pressure on PM RT than did rates (Figures S6-S8). Ongoing-task thresholds explained more of the PM-induced cost to ongoing-task RT than did ongoing-task accumulation rates (Figure S9). Proactive control explained more of the effects on PM accuracy and PM RT than did reactive control (Figure S10).

General Discussion

We used a cognitive model of event-based Prospective Memory (PM) based on an evidence-accumulation decision processing framework, Strickland et al.'s (2018) PM Decision Control (PMDC) model, to investigate how cognitive control and cognitive capacity mechanisms interact and enable participants to adapt to the demands of a complex and demanding air traffic control conflict detection task. We proposed a new quantitative approach to formalize the idea of cognitive capacity in evidence-accumulation models in general, and PMDC in particular, in terms of *gain*, a broadly-tuned amplification mechanism, and *focus*, a more finely-tuned relative modulation mechanism controlling signal-to-noise ratios, consistent with both early conceptions of visual attention (e.g., Posner & Boies, 1971) and more recent computational neuroscience divisive normalization approaches (e.g., Busse, et al. 2009; Carandini & Heeger, 2012; Heeger, 1992; Reynolds & Heeger, 2009; Schwartz & Simoncelli, 2001).

The conflict detection task manipulated time pressure and PM load (i.e., whether or not participants had to remember to perform a deferred task action) within subjects, with a between subjects task priority manipulation using instructions to emphasise either the accuracy or speed of the ongoing (conflict detection) task, the accuracy of the PM task, or neutral instructions that replicated Boag et al. (2019). Our experimental design had the low measurement error necessary to precisely characterize individual performance (Kolossa & Kopp, 2018; Smith & Little, 2018), with each participant performing more than one thousand decisions that each took several seconds, and also included a large number of participants, 60 or more in each instructional condition, required to support powerful between-subjects inferences and the generality of our results across individuals. Hence, this design allowed the use of approximately 80 estimated model parameters per participant to provide a fine-grained description of performance in terms of a detailed characterisation of cognitive processes, revealing a complex interplay between cognitive control and our new conception of cognitive capacity.

We found that cognitive control flexibly allocated cognitive capacity in order to manage the competing demands of time pressure, PM load, and task priority. Focus, as measured by the quality of the mean rate of evidence accumulation (i.e., the difference between rate for the accumulator that matches the ongoing task stimulus and the accumulator that mismatches it) was primarily influenced by task importance. Cognitive gain, which selectively determines the quantity of evidence accumulation (i.e., the sum of the mean rates for matching and mismatching accumulators) was primarily influenced by time pressure and PM load. Further, in a comparison across instructional manipulations, we confirmed a specific prediction of the new cognitive capacity framework, that increased focus not only increases quality, but also decreases quantity.

In some cases, our results supported trade-offs between ongoing and PM tasks that implicate capacity sharing (Navon & Gopher, 1979), a key marker of human performance being determined by a limited pool of cognitive capacity. In other cases, participants were able to mobilize extra capacity, and in general the greatest capacity was allocated to the highest priority task (see Walter & Meier, 2014, for a review of related findings). Our formal approach addresses Navon's (1984) critique of the circularity of the concept of capacity, by embedding it within a comprehensive model of task performance that takes account of human adaptations to task demands through proactive and reactive control processes (Braver, 2012), and which grounds the concept of capacity in well-defined and specific measures of latent information processing rates.

We found that the PMDC model was able to fit the full distribution of RTs for both ongoing-task and PM responses across all experimental factors, accounting for observed differences in accuracy and RT related to time pressure, PM demand, and task importance. Although there was a clear role for capacity sharing and capacity mobilization mechanisms, we also replicated previous work using an ongoing conflict detection task and other demanding ongoing tasks (Boag et al., 2019; Strickland et al., 2019), and less demanding ongoing tasks such as lexical decision (Ball & Aschenbrenner, 2017; Heathcote et al., 2015; Horn & Bayen, 2015; Strickland et al., 2017, 2018), in finding that proactive and reactive control processes explained the majority of variation in performance (however, as will be discussed, cognitive gain and focus play critical roles in explaining certain effects). Hence, we first summarize our findings with respect to cognitive control effects in order to provide an appropriate context for a more detailed consideration of capacity-related effects.

Cognitive Control

Proactive. Participants set lower ongoing task thresholds as time pressure increased, consistent with work showing individuals set lower thresholds to favour fast responding when deadlines are short (i.e., a speed-accuracy trade-off) (Boag et al., 2019; Dutilh, Wagenmakers, Visser, & van der Maas, 2011; Forstmann et al., 2011; Usher, Olami, & McClelland, 2002). Consistent with prior modeling of PM costs (e.g., Ball & Aschenbrenner, 2017; Boag et al., 2019; Heathcote et al., 2015; Horn & Bayen, 2015; Strickland et al., 2017, 2018), participants set higher ongoing task thresholds in PM blocks than control blocks, which drove PM cost effects and increased the frequency of non-responses (in PM blocks).

PM-induced proactive control interacted with time pressure. That is, participants used less proactive control as time pressure increased, making the ongoing task accumulators more likely to pre-empt the PM response. This resulted in poorer PM accuracy and more frequent non-responses in high time pressure PM blocks, consistent with prior work suggesting individuals are particularly prone to making PM errors during periods of heightened time pressure (Boag et al., 2019). Proactive control also depended upon the importance of the PM task relative to the ongoing task. As expected, the PM-important group used the largest amount of proactive control (i.e., proactive control was stronger when the PM task was emphasized; replicating Strickland et al., 2018) and the ongoing- and speed-important groups used the least.

PM thresholds decreased with increased time pressure and were reliably lower for the PM-important group, consistent with the increase in PM false alarms observed in that group, and in line with previous modeling (Strickland et al., 2018). This shows that participants proactively controlled PM decision processes to adapt PM task performance to the time pressure and reward structure of the environment.

Overall, these effects support a proactive control account in which participants control ongoing task and PM thresholds in order to facilitate fast responding as well as to increase the probability of responding to high- versus low-importance stimuli. However, as noted, this strategy can increase non-response misses (under high time pressure) and increase PM false alarms (when PM is prioritised), which may have implications in settings where such outcomes are undesirable.

Reactive. Ongoing task accumulation rates were lower on PM trials than on non-PM trials (i.e., rates were lower with a PM target present versus absent), consistent with inhibition from the PM detector when activated by a PM stimulus (Boag et al., 2019; Strickland et al., 2017, 2018). Inhibiting ongoing task rates on PM trials increases the probability that the PM accumulator will out-pace the ongoing task accumulators. This is in line with theoretical work (Bugg et al. 2013), neurological data (McDaniel et al. 2013), and broader approaches to human error (Norman, 1981; Reason, 1990) suggesting such response inhibition is necessary to allow atypical task responses (with weak associative strengths) to compete with common task responses (with strong associative strengths) for retrieval and response selection.

Time pressure had no systematic effect on the strength of reactive control, in line with Braver's (2012) description of reactive control as an automatic, stimulus-driven control process. Since reactive control is only active on PM trials, it would not be an effective mechanism for dealing with changes in time pressure across entire blocks of trials.

Reactive control was strongest in the PM-important group and weakest in the ongoing-important group (replicating Strickland et al., 2018), suggesting that individuals can modulate the strength with which irrelevant task information is inhibited depending on the reward structure of the environment. This is consistent with neurological work showing that reward motivations can increase the strength of reactive response inhibition (Boehler et al., 2014). In terms of our model, participants may adjust the reactive control inputs to ongoing task accumulators, depending on the importance of the PM task. That is, participants may set their reactive control architecture in anticipation of the upcoming reward context to favour stronger inhibitory control when a PM item is encountered.

Cognitive Capacity

Gain. The quantity of ongoing-task processing increased under both time pressure and PM load, supporting the idea that greater task demands lead to heightened cognitive gain (i.e., gain increased at shorter trial deadlines and under PM load; Boag et al., 2019). Ongoing-task quantity was highest for the speed-important group and lowest for the ongoing-important group (i.e., where ongoing task focus was highest), confirming our framework's prediction that quantity should be a decreasing function of focus. These effects are consistent with prior modeling (Rae et al., 2014) and support our framework's formulation of cognitive gain as primarily controlling the speed of responding, in contrast to focus, which controls the signal-to-noise ratio of the evidence and is thus a primary determinant of accuracy.

Focus. Consistent with prior work (Boag et al., 2019; Rae et al., 2014), ongoing-task processing quality decreased under both time pressure and PM load, indicating that greater task demands lead to a loss of cognitive focus. However, in terms of effect size, quality was much less affected by time pressure and PM load ($Z \sim 5$) than was quantity ($Z \sim 30$). Ongoing task focus was lowest in the speed-important group compared with the other three importance conditions, consistent with previous reports of reduced quality during high versus low time pressure or when the speed of responding is emphasized (e.g., Heitz & Schall, 2012; Ho et al., 2012; Rae et al., 2014; Starns, Ratcliff, & McKoon, 2012; Vandekerckhove, Tuerlinckx, & Lee, 2008).

Taken together, these results suggest that increased time pressure and PM load lead to a loss of cognitive focus, which reduces the quality of information entering the decision process. This could occur because individuals focus on less diagnostic information under high time pressure and because PM processes draw focus away from the ongoing task. We further note that this is consistent with the observed cost to ongoing task accuracy in PM blocks, which was greatest when trial load and time pressure were high, and strongest in the PM-important group. This contrasts with previous studies that found no capacity-sharing effects of PM load in less demanding ongoing tasks (Ball & Aschenbrenner, 2017; Heathcote et al., 2015; Horn & Bayen, 2015; Strickland et al., 2017, 2018), further highlighting that PM-induced costs to ongoing-task processing can occur in paradigms where the ongoing task is sufficiently demanding so as to fully occupy cognitive resources.

Consistent with our formulation of quality as measuring cognitive focus, quality was a sliding function of importance, with ongoing task focus highest in the ongoing-important group and lowest in the speed-important group, with the neutral and PM-important groups in between. In addition, ongoing task focus was marginally lower in the PM-important group compared with the neutral instruction group in PM blocks but not control blocks (i.e., ongoing task focus was lower only when the PM intention was active). This selective influence provides a further demonstration of capacity sharing: PM-important instructions produced the greatest amount of resource sharing from the ongoing task to the PM task, but only when the PM intention was active. When the PM intention was inactive (i.e., in control blocks) the quality of ongoing-task processing was the same as under neutral-importance instructions. These findings extend work from the basic PM literature in which emphasizing the importance of the PM task did not reduce the quality of ongoing-task processing (Strickland et al., 2018), and are consistent with the idea that the degree to which the ongoing and PM tasks share cognitive capacity is proportional to their relative importance (Walter & Meier, 2014).

PM Accumulation Rate. PM accumulation rates decreased as time pressure increased. Recall that ongoing-task quantity *increased* as time pressure increased. This trade-off suggests that resources were diverted from PM processing to ongoing-task processing in order to cope with the greater demands associated with performing the ongoing task under high time pressure (i.e., with a shorter trial deadline), a critical demonstration of capacity sharing (Navon & Gopher, 1979). However, time pressure did not affect PM rates in the speed-important group, which likely reflects that group's overall emphasis on responding quickly to avoid non-responses. Time pressure similarly did not affect PM rates in the PM-important group, which likely reflects the significantly greater cognitive capacity available to the PM task when it was emphasized, consistent with previous modeling (e.g., Strickland et al., 2018).

Compared with the neutral group, PM rates were higher in the PM-important group and lower in the ongoing- and speed-important groups. This second trade-off further demonstrates capacity sharing: resources were shared between the ongoing and PM tasks based on their relative importance (i.e., the greatest cognitive capacity was allocated to the highest priority task). The greater resources allocated to PM processing under PM-important instructions likely explains why ongoing-task quantity was lower under PM-important instructions compared with neutral, despite focus being directed away from the ongoing task (recall that quantity is a *decreasing* function of focus). That is, the 'missing' ongoing task resources were allocated to PM processing.

Consistent with ecological rationality approaches to cognition (Simon, 1956; Todd & Gigerenzer, 2007), these findings demonstrate that individuals allocate cognitive resources between the ongoing and PM tasks based on the reward and demand structure of the environment. Our framework provides a cogent explanation for this complex set of empirical phenomena that would be difficult to interpret using standard statistical analyses of observed behaviour. Moreover, the trade-offs between PM and ongoing task rates (i.e., by time pressure and task importance) revealed by our model provide two critical demonstrations of capacity sharing (Navon & Gopher, 1979) that do not suffer from circularity or unfalsifiability (Navon, 1984).

Trial Load Effects

Ongoing task RTs were marginally slower, and non-responses less frequent, under high trial load compared with low trial load when comparing conditions with equal time pressure. There were no significant effects of trial load on ongoing task accuracy, PM accuracy, or PM RT. In terms of the model, however, higher trial load was associated with poorer processing quantity, better processing quality, smaller proactive control effects, and lower PM accumulation rates. This is consistent with slightly more cognitive capacity being focused on the ongoing task versus the PM task during 20-second/5-decision trials compared with 8-second/2-decision trials, despite there being equal time available per decision on average. A possible explanation for this is that there was a fixed start-up time on each trial, which would have left more subsequent processing time on 20-second/5-decision trials compared with 8-second/2-decision trials. We note that this pattern of effects is similar to the differences that occurred between the ongoing- and PM-important groups (discussed below), which suggests that the less temporally-demanding context of the 20-second/5-decision trials led participants to focus more on the ongoing task relative to the PM task (i.e., to treat the ongoing task as more important) than they did in 8-second/2-decision trials. Nevertheless, we emphasize that the effects of trial load were extremely small in comparison to the effect of the time per decision, which was the major determinant of time pressure effects.

Summary of Between-Subjects Importance Effects

Confirming our framework's formulation of gain as a decreasing function of focus that primarily controls the speed of responding, ongoing-task quantity was lowest when the ongoing task was important (i.e., where focus was greatest) and highest when the speed of responding was important. As mentioned, ongoing-task quantity was lower than expected under PM-important instructions (compared with neutral), since directing focus away from the ongoing task (i.e., decreasing focus) should *increase* quantity. However, the concomitant increase in PM accumulation under PM-important instructions explains this via capacity sharing, that is, the 'missing' ongoing task resources were diverted to PM processing) (Navon & Gopher, 1979).

Quality was a sliding function of importance, consistent with participants shifting cognitive focus between concurrent tasks in accordance with the reward structure of the environment (i.e., attention was allocated in proportion to the importance of each task; Walter & Meier, 2014). Similarly, the PM-important group used the largest amount of proactive control and had the highest PM accumulation rates, while the ongoing- and speed- important groups used the least amount of proactive control and had the lowest PM accumulation rates. These effects were reflected in higher PM accuracy and slower ongoing task RTs observed in the PM-important group compared with lower PM accuracy and faster ongoing task RTs in the ongoing- and speed-important groups. The PM-important group also set lower PM thresholds than the other three groups, which was evident in the PM-important group's faster empirical PM RTs and significantly more frequent PM false alarms and non-responses. Average ongoing task and PM thresholds were lowest in the speed-important group, which also had the fastest ongoing task RTs and lowest frequency of non-response misses.

Non-decision time was also shortest in the speed-important group, which is consistent with previous modeling showing reduced non-decision time in response to heightened time pressure (e.g., Dambacher & Hübner, 2015) and is typically assumed to reflect a combination of faster motor response execution and more efficient pre-decisional attentional selection (e.g., Ong, Sewell, Weekes, McKague, & Abutalebi, 2017; Ratcliff & Smith, 2010; Voss et al., 2010). Non-decision time was longest in the PM-important group, which may reflect additional processing related to the PM task that is not part of the evidence accumulation process, such as double-checking or pre-decisional visual search. Reactive control was also strongest in the PM-important group, and weakest in the ongoing-important group, demonstrating that task importance modulates the strength with which irrelevant task information is inhibited (Strickland et al., 2018).

Taken together, these findings demonstrate that cognitive control and cognitive gain and focus mechanisms each contribute to explaining the complex ways the cognitive system adapts to environmental demands to support decision making. However, we repeat that the capacity effects were small in comparison to the proactive and reactive cognitive control effects we found here and in previous work (e.g., Boag et al., 2019; Heathcote et al., 2015; Strickland et al., 2017, 2018). Specifically, model exploration showed that ongoing-task thresholds explained more of the effects on PM accuracy, PM RT, and PM-induced costs to ongoing-task RT than did ongoing-task accumulation rates (Figures S9-S10), whereas ongoing-task accumulation rates were more important in explaining the effects of time pressure on ongoing-task RT than were ongoing-task thresholds. As such, although cognitive gain and focus are clearly useful concepts, they should be situated within a cognitive control framework to form a complete picture of the latent cognitive processes that control overt performance.

General Implications

This current work provides a significant theoretical advance, by offering a tractable quantitative framework for measuring the complex set of cognitive control and cognitive capacity processes that underlie performance in complex dynamic environments. More broadly, our approach has the potential to provide insights into cognitive control and attention deficits observed in certain clinical disorders including anxiety, depression, schizophrenia, and substance dependence and abuse disorders (see White, Ratcliff, Vasey, & McKoon, 2010). For example, individuals with high anxiety preferentially direct attention toward threatening information, a phenomenon known as *attentional bias* (see Bar-Haim, Lamy, Pergamin, Bakermans-Kranenburg, & Van Ijzendoorn, 2007). Current debate exists over the specific source of such biases (e.g., early-stage attentional selection processes versus late-stage maintenance or failures to disengage attention; see Bar-Haim et al., 2007). Our proactive and reactive control, cognitive gain and focus, and non-decision time measures could prove useful in resolving these and similar theoretical issues in clinical psychology. Proactive and reactive cognitive control deficits are also thought to underlie the behavioural disorganization characteristic of schizophrenia (see Lesh, Niendam, Minzenberg, & Carter, 2011; Lesh et al., 2013) and have been implicated in ADHD (Iselin & DeCoster, 2009; Pani et al., 2013). The PMDC model provides a cogent framework for understanding a complex set of empirical phenomena that would be difficult to interpret using standard statistical analyses of observed behaviour. In providing a detailed understanding of the cognitive processes thought to underlie many clinical disorders, our model could be used to improve assessment, classification, and treatment.

In work and everyday life, people are particularly prone to disruption from concurrent tasks that compete for their limited attention. Our approach may thus prove useful for measuring the disruptive effects of distractions and interruptions[6] on attention and performance (Altmann, Trafton, & Hambrick, 2014; Monk, Boehm-Davis, Mason, & Trafton, 2004; Trafton & Monk, 2007; Wilson, Farrell, Visser, & Loft, 2018). Distractions (i.e., when attention is partially diverted from the primary task; Graydon & Eysenck, 1989) and interruptions (i.e., when attention is entirely diverted from the primary task; Gillie & Broadbent, 1989) have been linked to negative outcomes in safety-critical contexts including aviation (Dismukes, Young, Sumwalt III, & Null, 1998; Loukopoulos, Dismukes, & Barshi, 2001, 2003), driving (Bowden, Loft, Wilson, Howard, & Visser, 2019; Ratcliff & Strayer, 2014; Strayer et al., 2015), and medicine (Coiera & Tombs, 1998; Tucker & Spear, 2006). For example, a ringing mobile phone can draw cognitive focus away from the road scene, leading to slower braking times and more severe lane deviations (Ratcliff & Strayer, 2014; Waard & Brookhuis, 1997) (see Averty, Collet, Dittmar,

[6] Dodhia and Dismukes (2009) have argued that interruptions are essentially one-off PM tasks, in which an intention to resume the interrupted task must be formed, stored, and later retrieved once the interruption is over.

Athènes, & Vernet-Maury, 2004; Metzger & Parasuraman, 2001; for examples from air traffic control). Although it may be challenging to achieve the experimental control and number of trials required for model fitting, our approach could prove useful in such contexts, giving a comprehensive decomposition of cognitive capacity and the sources of attentional degradation.

Limitations and Future Directions

One limitation of our modelling approach is that we do not include an explicit memory mechanism, so our model makes no claims about how PM intentions are stored, retrieved, or forgotten. Forgetting irrelevant and outdated information is critical in dynamic task environments in which to-be-remembered information changes frequently (Garland, Stein, & Muller, 1999; Hopkin, 1980). PM in air traffic control, for example, often involves a dynamic process of coordination between controllers and pilots, meaning intentions are encoded and updated on a moment-to-moment basis (Loft, Smith, & Bhaskara, 2011) rather than a single fixed intention encoded at the beginning of a trial. Failing to forget outdated PM intentions has been shown to cause PM commission errors and increase susceptibility to PM lures (i.e., non-PM items that share features with genuine PM targets; e.g., Meier, Zimmermann, & Perrig, 2006; Scullin, Bugg, & McDaniel, 2012). As such, although our approach provided a comprehensive and theoretically informative account of a complex set of data, the present modeling necessarily omitted some processes likely to be consequential in real work systems.

Extending the model to include explicit mechanisms of retrieval/forgetting could prove useful for investigating situations in which PM errors are expected to be due to retrieval failures. Retrieval failures are likely to occur when PM processing is interrupted and must then be resumed (Wilson et al., 2018), when PM retrieval must be triggered internally (as in time-based

PM tasks; e.g., Huang, Loft, & Humphreys, 2014), and when individuals lack information about the context in which PM events will occur (Loft, Finnerty et al., 2011). Adding a retrieval/forgetting mechanism to the model could also provide insight into how people manage tasks with multiple concurrent PM intentions (e.g., Cohen, Jaudas, & Gollwitzer, 2008; Einstein & McDaniel, 2005) and intentions that require updating over time (Bugg & Scullin, 2013; Ecker, Lewandowsky, Oberauer, & Chee, 2010; Ecker, Oberauer, & Lewandowsky, 2014; Voigt et al., 2014). We expect environments with multiple PM tasks and intention-updating to be even more demanding than our task and to therefore elicit greater effects on the attentional system than seen here. Another possibility with less-demanding tasks is that, as demands increase, participants may simultaneously increase their effort toward both the ongoing and PM tasks due to focusing more on the entire task ensemble (Rummel, Smeekens, & Kane, 2017). In the model this would be reflected by concurrent increases in both ongoing task quality and PM accumulation rate. Although not observed in the context of our demanding ongoing task and non-focal PM stimuli, future work could pair our model with a simultaneous detection response task, which has been used to measure overall on-task focus and modelled using evidence-accumulation processes (Cooper, Castro, & Strayer, 2016).

In terms of methodology, on PM trials, our task required participants to make PM responses *instead* of the ongoing task response. This was done because a common form of PM error in complex work tasks is due to ‘habit capture’, where an individual fails to perform an atypical intended action, substituting a routine non-intended action instead (Grundgeiger, Sanderson, & Dismukes, 2015; Loft & Remington, 2010; Norman, 1981; Reason, 1990). For example, a thunderstorm may mean that a controller cannot assign aircraft a certain range of altitude. It may be the case that 767 aircraft are routinely assigned altitude 320, but in this case, the controller must assign an alternative altitude. However, we note that this mode of responding differs from the 'dual-response' PM paradigm (e.g., Bisiacchi et al., 2009), in which participants are instructed to make PM responses in addition to the ongoing response. Heathcote et al. (2015) reported similar proactive control effects in a dual-response paradigm. However, PM trials have not yet been modeled in a dual-response PM paradigm so it is unclear whether reactive control and capacity allocation processes will operate exactly as they did here. We note that this represents a difficult modeling problem, since RTs for the ongoing and PM responses are confounded in the dual-response case.

Our task used highly non-focal PM items, meaning the evidence required to make a PM decision was unrelated to the evidence required to make ongoing task (conflict detection) responses. Focal PM items, which share features with ongoing task stimuli and are thus more salient, are typically assumed to require less PM monitoring than non-focal items (Einstein & McDaniel, 2005; McDaniel & Einstein, 2000), and some researchers argue are more likely to result in 'spontaneous retrieval' (Einstein et al., 2005) in which intentions are retrieved without effortful processing. In addition, Strickland et al. (2018) reported that focal PM items resulted in stronger reactive control over ongoing task accumulation rates than did non-focal items, due to focal PM items eliciting greater activation of the PM detector and consequently greater inhibition of the ongoing task accumulators. Thus, we would expect focal PM items to produce faster PM accumulation rates, smaller capacity-sharing effects, and larger reactive control effects than occurred with our non-focal PM task.

Another important consideration is that (due to practical and measurement considerations) our task, although within the bounds of previous PM research, used a relatively high frequency of PM items (20% of PM block trials). With a lower PM frequency, we would expect less PM cost (e.g., Loft, Kearney, & Remington, 2008) and thus weaker proactive control effects than seen here. Low-frequency PM may also result in 'trigger-failures' (Matzke, Love, & Heathcote, 2017) - trials on which the PM intention is not retrieved and thus the PM accumulator does not enter the race. Extending the model to include a trigger-failure mechanism would be an interesting avenue for future work.

Finally, our conception of mean rates as being a function of cognitive gain and focus could potentially be of use in broader applications of evidence accumulation models. For example, future work could directly estimate gain and focus parameters along with parameters quantifying the bottom-up components of information processing. If it can be assumed that the bottom up components are invariant over a sufficient set of experimental conditions, such models can be made identifiable when the total number of gain, focus and bottom up parameters is at least equal to the number of parameters required in a traditional parameterization (e.g., the number of conditions times the number of accumulators required to model them). Where the number is less, the more specific predictions of the focus and gain framework can be compared to those of a traditional, and more flexible, parameterization in order to test which provides the best trade-off between goodness-of-fit and parsimony. Selective influence assumptions can also be tested and, as here, an assessment made of predicted trade-offs, such as an increase in quality and decrease in quantity due to an increase in focus.

Conclusion

This study presented a formal justification for measuring and interpreting cognitive gain and focus effects in an evidence-accumulation modeling framework. The model provided a consistent and psychologically interpretable quantitative measure of cognitive control and cognitive capacity effects for use in a dynamic multiple-task environment. Consistent with previous work, we found robust capacity-sharing and cognitive control effects, highlighting the role of each in adapting to the particular time pressure, PM, and task importance requirements of the environment. Extending previous work, we found that resources were shared between the ongoing and PM tasks in proportion to their relative importance (i.e., the greatest cognitive capacity was allocated to the highest priority task). Further, we decomposed capacity into distinct cognitive gain and focus mechanisms to give a finer-grained picture of the role of the attentional system in supporting decision making and PM. This work has the potential to be useful to researchers in many different fields, providing a comprehensive computational framework to test cognitive theory and measure the latent cognitive control and attentional processes that drive performance in complex multiple-task environments.

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